Pushing the Limits of Zero-shot End-to-End Speech Translation

Anonymous ACL submission

Abstract

Data scarcity and the modality gap between the speech and text modalities are two major obstacles of end-to-end Speech Translation (ST) systems, thus hindering their performance. Prior work has attempted to mitigate these challenges by leveraging external MT data and optimizing distance metrics that bring closer the speech-text representations. However, achieving competitive results typically requires some ST data. For this reason, we introduce ZEROSWOT, a method for zero-shot ST that bridges the modality gap without any paired ST data. Leveraging a novel CTC compression and Optimal Transport, we train a speech encoder using only ASR data, to align with the representation space of a massively multilingual MT model. The speech encoder seamlessly integrates with the MT model at inference, enabling direct translation from speech to text, across all languages supported by the MT model. Our experiments show that we can effectively close the modality gap without ST data, while our results on MUST-C and COVOST demonstrate our method's superiority over not only previous zero-shot models, but also supervised ones, achieving state-of-the-art results.[1]

1 Introduction

Traditionally, the standard approach for Speech translation (ST) has been the cascade model (Ney, 1999; Mathias and Byrne, 2006), where Automatic Speech Recognition (ASR) and Machine Translation (MT) systems were chained together to produce the desired output. However, in recent years, there has been a paradigm shift towards end-to-end models, which aim to directly map the input speech to the target text without the intermediate transcription step (Bérard et al., 2016). Such models offer several advantages, including reduced error propagation, more compact architectures, and faster inference times (Sperber and Paulik, 2020).

[1]Code and models will be available here.

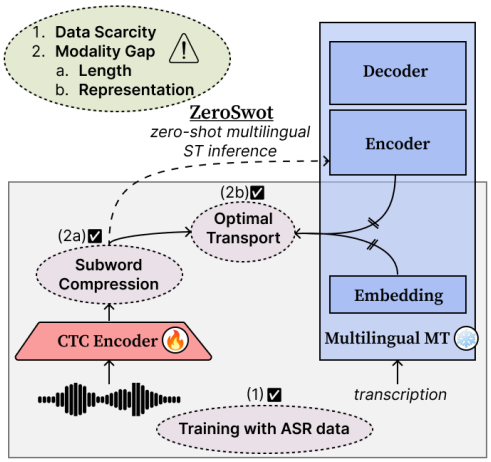

Figure 1: Proposed Zero-shot Speech Translation

Despite their advantages, end-to-end models require parallel ST data, which are often limited. To mitigate this *data scarcity*, several strategies aim to leverage the more abundant ASR and MT data (Bérard et al., 2018; Anastasopoulos and Chiang, 2018). Then, another challenge that arises is the *modality gap*, which emerges from the inherent differences between the speech and text modalities, manifesting in *length mismatch* and *representation mismatch*. Convolutional Length Adapters (Li et al., 2021) or Connectionist Temporal Classification (CTC) (Graves et al., 2006; Liu et al., 2020) can alleviate the length mismatch to some extent. To ease the representation gap, previous works have proposed a shared encoder (Ye et al., 2021) and optimizing distance metrics to bring the speech-text representation closer to the shared semantic space (Fang et al., 2022; Ye et al., 2022). Due to its ability to handle representations of different lengths, the Wasserstein distance (Frogner et al., 2015) using Optimal Transport, has emerged as an effective distance metric, specifically during pretraining (Le et al., 2023; Tsiamas et al., 2023). Although these methods show promise in reducing the modality gap and increasing translation quality, they still require at least some ST data.

To this end, we propose Zero-shot ST with Subword compression and Optimal Transport (ZEROSWOT), a novel approach that aims to bridge the modality gap in a zero-shot fashion, only requiring ASR and MT data. Using Optimal Transport, we train a speech encoder based on WAV2VEC 2.0 (Baevski et al., 2020) to produce representations akin to the embedding space of a massively multilingual MT model, thus enabling zero-shot ST inference across all its supported target languages (Fig. 1). To map the two embedding spaces, our method learns the tokenization of the MT model through CTC, and compresses the speech representations to the corresponding subwords, thus closing the length mismatch. Experiments on MuST-C (Cattoni et al., 2021) reveal that our method is not only better than existing zero-shot models, by a large margin, but also surpasses supervised ones, achieving state-of-the-art results. On CoVoST (Wang et al., 2020b), ZEROSWOT outperforms the original version of the multimodal SEAMLESSM4T (Seamless-Communication, 2023a), while evaluations on the 88 target languages of FLEURS (Conneau et al., 2023) showcase the massively multilingual capacity of our method. ZEROSWOT is also vastly superior to comparable CTC-based cascade ST models, and while it is on par with cascades that utilize strong attention-based encoder-decoder ASR models, it ranks better in terms of efficiency. Finally, we provide evidence of our method's ability to close the modality gap, both in terms of length and representation.

2 Relevant Research

2.1 End-to-end Speech Translation

Data Scarcity. To alleviate data scarcity, end-to-end ST methods usually utilize the more abundant data of ASR and MT. Such methods include pretraining (Bérard et al., 2018; Bansal et al., 2019; Wang et al., 2020a; Alinejad and Sarkar, 2020), multi-task learning (Anastasopoulos and Chiang, 2018; Indurthi et al., 2021), data augmentation (Jia et al., 2019; Pino et al., 2019; Lam et al., 2022; Tsiamas et al., 2022a), and knowledge distillation (Liu et al., 2019; Gaido et al., 2020). Recently, many methods indirectly leverage external data through large foundation models (Bommasani et al., 2022), like WAV2VEC 2.0 (Baevski et al., 2020), MBART50 (Tang et al., 2020), and LLaMa2 (Touvron et al., 2023), which were used in (Ye et al., 2021; Han et al., 2021; Tsiamas et al., 2022b; Zhang et al., 2023). Similarly, here we utilize WAV2VEC 2.0 and NLLB (NLLB et al., 2022).

Modality Gap. Implicit alignment techniques to bridge the representation gap involve a shared semantic encoder in a multitasking framework (Liu et al., 2020; Ye et al., 2021; Tang et al., 2021b), which can be improved by mixup (Fang et al., 2022; Zhou et al., 2023). In addition, explicit alignment methods optimize a distance metric to bring the speech-text representations closer in the shared semantic space. Such distance metrics include the euclidean (Liu et al., 2020; Tang et al., 2021a), cosine (Chuang et al., 2020), and contrastive (Ye et al., 2022; Ouyang et al., 2023), but they typically require some transformation in the representations, such as mean-pooling, while our approach optimizes a distance that does not alter the representation space. Methods to reduce the length discrepancy usually include sub-sampling the speech representation using convolutional length adaptors (Li et al., 2021; Gállego et al., 2021; Fang et al., 2022; Zhao et al., 2022) or character/phoneme-based CTC compression (Liu et al., 2020; Gaido et al., 2021; Xu et al., 2021a). Several methods have also used phonemized text in order to better match the representations in both length and content (Tang et al., 2021a, 2022; Le et al., 2023), but potentially limiting the quality of the text branch due to noise. In this work, we introduce a novel CTC-based compression to subword units, directly aligning with the tokenization of MT models.

2.2 Optimal Transport

Optimal Transport (OT) (Peyré and Cuturi, 2019), traditionally used in NLP and MT (Chen et al., 2019; Alqahtani et al., 2021), has recently found its way into ST. Zhou et al. (2023) used OT to find the alignment between speech and text features to apply Mixup. Le et al. (2023) applied OT in a siamese pretraining setting in combination with CTC, yielding improvements compared to the standard ASR pretraining. Tsiamas et al. (2023) extended this pretraining in the context of foundation models, while also freezing the text branch for better integration with the text decoder during ST finetuning. Here, we also follow the siamese paradigm, but as a means of directly integrating the speech encoder to the text space without ST finetuning.

2.3 Zero-shot Speech Translation

Escolano et al. (2021b) were the first to achieve zero-shot ST, by incorporating a speech encoder

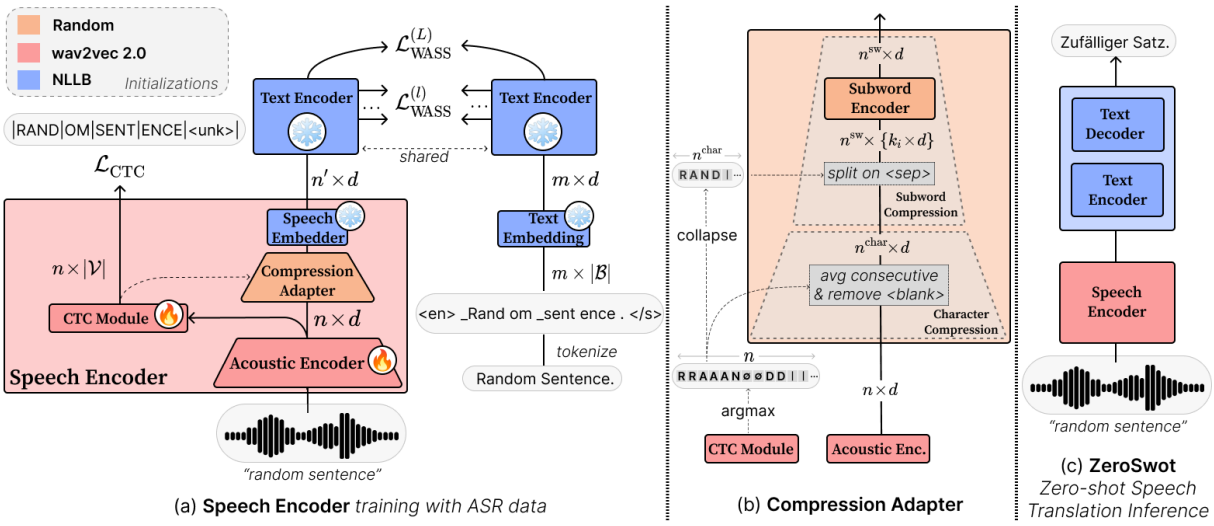

Figure 2: Methodology: Speech Encoder Training, Compression Adapter, and Inference with ZEROSWOT.

to the representation space of an MT model using language-specific encoders-decoders (Escolano et al., 2021a). Dinh et al. (2022) combined multi-task learning on ASR and MT, introducing an auxiliary loss to minimize the euclidean distance between mean-pooled speech and text representations. T-modules (Duquenne et al., 2022) harnessed mined data to learn a fixed-size multilingual and multimodal representation space, subsequently enabling zero-shot ST encoding and decoding from that space. DCMA (Wang et al., 2022) projects both speech and text into a fixed-length joint space using an attention-driven shared memory module, after which it enforces the speech distribution of a codebook to closely mirror its textual counterpart. Finally, Gao et al. (2023b) proposed a strategy that employs a multimodal variant of cross-lingual consistency regularization (Gao et al., 2023a), training a model with WAV2VEC 2.0 and a shared encoder on both MT and ASR data. Here we leverage the massively multilingual representation space of an MT model, and adapt to it speech representations with Optimal Transport, after compressing them using the tokenization of the MT space.

3 Methodology

3.1 Problem Definition & Proposed Solution

End-to-end Speech Translation. A speech translation corpus consists of speech-transcription-translation triplets, $\mathcal{D} = \{(\mathbf{s}, \mathbf{x}, \mathbf{y})\}$, where $\mathbf{s}$ is the speech signal, $\mathbf{x}$ is the transcription, and $\mathbf{y}$ the translation. End-to-end ST systems aim to learn a model $\mathcal{M}^{\text{ST}}$ that generates the translation $\mathbf{y}$ directly from the speech $\mathbf{s}$, using the parallel ST data $\mathcal{D}^{\text{ST}} = \{(\mathbf{s}, \mathbf{y})\}$. The transcription $\mathbf{x}$ is optionally utilized, as in pretraining or multi-task learning.

Zero-shot Speech Translation. In a zero-shot ST setting, we aim to learn a model $\mathcal{M}^{\text{ZS-ST}}$ that generates the translation $\mathbf{y}$ with access to corpora $\mathcal{D}^{\text{MT}} = \{(\mathbf{x}, \mathbf{y})\}$ and $\mathcal{D}^{\text{ASR}} = \{(\mathbf{s}, \mathbf{x})\}$, but without directly utilizing the parallel corpus $\mathcal{D}^{\text{ST}}$.

Proposed Solution. Assuming access to an MT model $\mathcal{M}^{\text{MT}}$ obtained via $\mathcal{D}^{\text{MT}}$, we utilize $\mathcal{D}^{\text{ASR}}$ to learn a speech encoder **S-Enc** that produces representations akin to those expected by $\mathcal{M}^{\text{MT}}$. On inference time, we achieve zero-shot ST by replacing the embedding layer of $\mathcal{M}^{\text{MT}}$ with **S-Enc**.

3.2 Model Architecture

Our model architecture includes a speech and a text branch. The text branch consists of a text encoder, which remains frozen during training. The speech branch consists of an acoustic encoder, a CTC module, a compression adapter, a speech embedder and a semantic encoder, of which the parameters are shared with the frozen text encoder (Figure 2a).

3.2.1 Text Encoder

The text encoder is a Transformer, of which the parameters are initialized from a massively multilingual MT model (NLLB et al., 2022), and kept frozen during training. The tokenized[2] source text $\mathbf{x}$ with length m is passed through an embedding layer $\mathbf{Emb}: |\mathcal{B}| \rightarrow d$ to obtain $\mathbf{e}^{\text{x}} \in \mathbb{R}^{m \times d}$, where $\mathcal{B}$ is a multilingual subword-level vocabulary. Sinusoidal positional encodings $\mathbf{Pos}(\cdot)$ are added after an up-scaling (Vaswani et al., 2017), and a Trans-

[2]With prepended <lang> and appended </s> tokens.

former encoder **T-Enc** with L layers is used to obtain a semantic representation $\mathbf{h}^{\text{x}}_L \in \mathbb{R}^{m \times d}$.

$$\mathbf{e}^{\text{x}} = \sqrt{d} \cdot \mathbf{Emb}(\mathbf{x}) + \mathbf{Pos}(m) \quad (1)$$

$$\mathbf{h}^{\text{x}}_L = \mathbf{T\text{-}Enc}(\mathbf{e}^{\text{x}}) \quad (2)$$

3.2.2 Acoustic Encoder

The acoustic encoder **A-Enc** takes as input the speech signal $\mathbf{s} \in \mathbb{R}^{\ell}$ and produces an acoustic representation $\mathbf{a} \in \mathbb{R}^{n \times d}$. It consists of a series of strided convolutional layers that downsample the signal by r (thus, $n = \ell/r$), followed by a Transformer encoder with N layers. It is initialized from WAV2VEC 2.0 and is finetuned during training.

$$\mathbf{a} = \mathbf{A\text{-}Enc}(\mathbf{s}) \quad (3)$$

3.2.3 Connectionist Temporal Classification

We use a CTC loss (Graves et al., 2006) to maintain a meaningful acoustic representation and provide the necessary information to the compression adapter (§3.2.4). A CTC module, which is a linear softmax layer produces probabilities $\mathbf{p} \in \mathbb{R}^{n \times |\mathcal{V}|}$, where $\mathcal{V}$ is a letter-based vocabulary.[3]

$$\mathbf{p} = \text{softmax}(\mathbf{a} \cdot \mathbf{W}^{\text{ctc}} + \mathbf{b}^{\text{ctc}}) \quad (4)$$

Where $\mathbf{W}^{\text{ctc}} \in \mathbb{R}^{d \times |\mathcal{V}|}$ and $\mathbf{b}^{\text{ctc}} \in \mathbb{R}^{|\mathcal{V}|}$ are trainable parameters, initialized from WAV2VEC 2.0.

Given the CTC labels $\mathbf{z}$, and their conditional probability $P(\mathbf{z}|\mathbf{p})$, which is obtained by summing over the probability of all possible alignment paths between the acoustic representation $\mathbf{a}$ and $\mathbf{z}$, the CTC loss is defined as:

$$\mathcal{L}_{\text{CTC}} = -\log P(\mathbf{z}|\mathbf{p}) \quad (5)$$

Separation	Punct.	CTC labels for *"Random Sentence."*
words	✗	R A N D O M | S E N T E N C E |
subwords	✓	R A N D | O M | S E N T | E N C E | <unk> |

Table 1: Standard vs proposed CTC labels example.

The labels $\mathbf{z}$ are usually obtained from the transcription $\mathbf{x}$ via splitting on words and removing characters absent from $\mathcal{V}$, such as punctuation. But this implies a word-level tokenization and text normalization, which is inconsistent with the text branch (§3.2.1). Thus, in order to minimize the discrepancies between the two branches, we propose to split on subwords using the text branch tokenizer, and keep the positions of characters not in $\mathcal{V}$, by replacing them with the unknown token (Table 1).

[3]Incl. *blank* <blank>, *unknown* <unk>, *separator* <sep>.

3.2.4 Compression Adapter

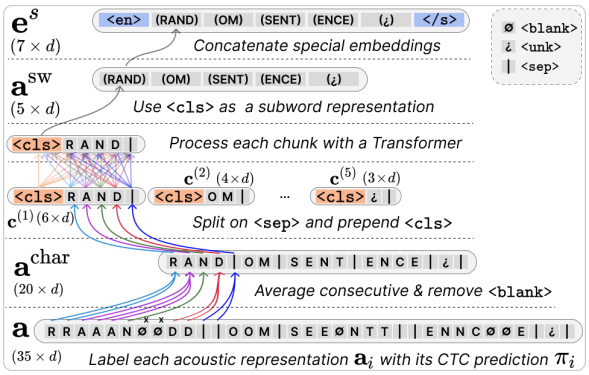

Figure 3: Example of our proposed compression.

The compression adapter (Fig. 2b) takes as input the acoustic representation $\mathbf{a}$ and the CTC probabilities $\mathbf{p}$, to produce a compressed acoustic representation $\mathbf{a}^{\text{sw}} \in \mathbb{R}^{n^{\text{sw}} \times d}$, where $n^{\text{sw}} \leq n$, that resembles in length and content the text embedding $\mathbf{e}^{\text{x}}$. It involves two stages: compression to characters (Liu et al., 2020), followed by a novel compression to subwords.

Character Compression. Each vector $\mathbf{a}_i \in \mathbb{R}^d$ of the acoustic representation is labeled according to the corresponding greedy CTC prediction $\pi_i = \text{argmax}(\mathbf{p}_i)$. Then, consecutive same-labeled representations are grouped together, and combined via mean-pooling, while removing those labeled as blanks, thus having a character-like representation $\mathbf{a}^{\text{char}} \in \mathbb{R}^{n^{\text{char}} \times d}$, where $n^{\text{char}} \leq n$. Similarly, $\mathbf{p}$ is compressed to $\mathbf{p}^{\text{char}} \in \mathbb{R}^{n^{\text{char}} \times |\mathcal{V}|}$.

$$\boldsymbol{\pi} = \text{argmax}(\mathbf{p}) \quad (6)$$

$$\mathbf{p}^{\text{char}} = \texttt{char-compress}(\mathbf{p}|\boldsymbol{\pi}) \quad (7)$$

$$\mathbf{a}^{\text{char}} = \texttt{char-compress}(\mathbf{a}|\boldsymbol{\pi}) \quad (8)$$

Subword Compression. The character representation $\mathbf{a}^{\text{char}}$ is split into chunks $\mathbf{c}^{(1)}, \ldots, \mathbf{c}^{(n^{\text{sw}})}$ according to the positions labeled as separators, where n^{sw} is the number of predicted separators, $\mathbf{c}^{(i)} \in \mathbb{R}^{k_i \times d}$ is the $i-$th chunk representation (with k_i number of characters), and $n^{\text{char}} = \sum_{i=0}^{n^{\text{sw}}} k_i$. Since the CTC is predicting the tokenization of the text branch through the proposed target labels, each chunk is combining information that resemble subword tokens from $\mathcal{V}$. Each chunk of character representations is processed independently with **Subword-Enc** : $\mathbb{R}^{k_i \times d} \rightarrow \mathbb{R}^d$, which is Transformer encoder that prepends a trainable <cls> token to each chunk, which is then used a subword representation of the whole chunk (Devlin

et al., 2019). Then, by concatenation we obtain a subword-like compressed representation $\mathbf{a}^{\text{sw}} \in \mathbb{R}^{n^{\text{sw}} \times d}$, where $n^{\text{sw}} \leq n^{\text{char}} \leq n$ (Fig. 3).

$$\mathbf{c}^{(1)}, \ldots, \mathbf{c}^{(n^{\text{sw}})} = \texttt{split}(\mathbf{a}^{\text{char}} | \boldsymbol{\pi}^{\text{char}}) \quad (9)$$

$$\mathbf{a}_i^{\text{sw}} = \textbf{Subword-Enc}\big(\mathbf{c}^{(i)}\big) \quad (10)$$

3.2.5 Speech Embedder

We concatenate to the compressed acoustic representation two vectors $\boldsymbol{\epsilon}^{\texttt{<lang>}}, \boldsymbol{\epsilon}^{\texttt{</s>}} \in \mathbb{R}^d$ that function as the source language and end of sentence embeddings. Similar to the text branch, we scale the representation by $\sqrt{d}$ and add sinusoidal positional encodings with $\textbf{Pos}(\cdot)$ (Eq. 1), thus obtaining a speech embedding $\mathbf{e}^{\text{s}} \in \mathbb{R}^{n' \times d}$, where $n' = n^{\text{sw}} + 2$. The special embeddings are initialized from the text embedding (Eq. 1), and remain frozen.

3.2.6 Semantic Encoder

The speech embedding $\mathbf{e}^{\text{s}}$ is passed through a Transformer encoder $\textbf{T-Enc}$, which is frozen and shared with the text branch (Eq. 2), to obtain a semantic speech representation $\mathbf{h}_L^{\text{s}} \in \mathbb{R}^{n' \times d}$.

$$\mathbf{e}^{\text{s}} = \sqrt{d}[\boldsymbol{\epsilon}^{\texttt{<lang>}}, \mathbf{a}^{\text{sw}}, \boldsymbol{\epsilon}^{\texttt{<s>}}] + \textbf{Pos}(n') \quad (11)$$

$$\mathbf{h}_L^{\text{s}} = \textbf{T-Enc}(\mathbf{e}^{\text{s}}) \quad (12)$$

3.3 Optimal Transport

To align a speech representation $\mathbf{h}^{\text{s}} \in \mathbb{R}^{n' \times d}$ to the text representation $\mathbf{h}^{\text{x}} \in \mathbb{R}^{m \times d}$, we are minimizing their Wasserstein loss (Frogner et al., 2015) using Optimal Transport (OT) (Peyré and Cuturi, 2019), as in Le et al. (2023); Tsiamas et al. (2023).

We assume two uniform probability distributions $\boldsymbol{\phi}^{\text{s}}, \boldsymbol{\phi}^{\text{x}}$, with $\boldsymbol{\phi}_i^{\text{s}} = 1/n'$ and $\boldsymbol{\phi}_j^{\text{x}} = 1/m$, that define the mass of each position in the speech and text representations. Using a squared euclidean cost function we obtain a pairwise cost matrix $\mathbf{C} \in \mathbb{R}_+^{n' \times m}$, where $\mathbf{C}_{ij} = ||\mathbf{h}_i^{\text{s}} - \mathbf{h}_j^{\text{x}}||_2^2$. Then, the Wasserstein distance $W_\delta \in \mathbb{R}_+$ is defined as the minimum transportation cost over all possible transportation plans $\mathbf{Z} \in \mathbb{R}_+^{n' \times m}$ of the total masses $\boldsymbol{\phi}^{\text{s}}, \boldsymbol{\phi}^{\text{x}}$. The optimization is thus subjected to constraints $\sum_{j=1}^{m} \mathbf{Z}_{:,j} = 1/n'$ and $\sum_{i=1}^{n'} \mathbf{Z}_{i,:} = 1/m$.

$$W_\delta = \min_{\mathbf{Z}} \sum_{i=1}^{n'} \sum_{j=1}^{m} \mathbf{Z}_{ij} \mathbf{C}_{ij} \quad (13)$$

In practice, to make the Wasserstein distance differentiable and efficient to compute using the Sinkhorn algorithm (Knopp and Sinkhorn, 1967), we use its entropy-regularized upper-bound estimation. Furthermore, since the Wasserstein distance is permutation invariant, we follow Le et al. (2023) and incorporate two positional regularization vectors $\mathbf{v}^{\text{s}} \in \mathbb{R}^{n'}$ and $\mathbf{v}^{\text{x}} \in \mathbb{R}^{m}$ in $\mathbf{h}^{\text{s}}$ and $\mathbf{h}^{\text{x}}$ accordingly, thus penalizing the transportation of mass between two distant positions i and j.

$$\bar{\mathbf{h}}^{\text{s}} = [\mathbf{h}^{\text{s}}; \mu \mathbf{v}^{\text{s}}] \text{ , where } \mathbf{v}_i^{\text{s}} = \frac{i-1}{n'-1} \quad (14)$$

$$\bar{\mathbf{h}}^{\text{x}} = [\mathbf{h}^{\text{x}}; \mu \mathbf{v}^{\text{x}}] \text{ , where } \mathbf{v}_j^{\text{x}} = \frac{j-1}{m-1} \quad (15)$$

And thus for the positional regularized cost matrix $\bar{\mathbf{C}}$, the upper-bound Wasserstein distance that we use as a loss function is defined as:

$$\mathcal{L}_{\text{WASS}} = \min_{\mathbf{Z}} \Big(\sum_{i=1}^{n'} \sum_{j=1}^{m} \mathbf{Z}_{ij} \bar{\mathbf{C}}_{ij} - \lambda \text{H}(\mathbf{Z}) \Big) \quad (16)$$

Where $\lambda > 0$ is a hyperparameter, and $\text{H}(\cdot)$ denotes the von Neumann entropy of a matrix.

3.4 Final Loss

We apply a Wasserstein loss (Eq. 16), not only at the final layer but also at intermediate ones, since they also carry important information, and can thus help producing more robust speech representations. Thus, the final loss is defined as:

$$\mathcal{L} = \sum_{l \in \mathcal{I}} \frac{\alpha}{|\mathcal{I}|} \mathcal{L}_{\text{WASS}}^{(l)} + (1-\alpha) \mathcal{L}_{\text{CTC}} \quad (17)$$

Where $\mathcal{I}$ is the set of shared encoder layers for which we apply Wasserstein losses, and $\alpha > 0$ is a hyperparameter to balance the relative importance between the Wasserstein and CTC losses.

3.5 Zero-shot Speech Translation Inference

To enable zero-shot ST inference, we simply replace the MT embedding layer with the trained speech encoder. (ZEROSWOT, Fig. 2c).

4 Experimental Setup

Data. For training we are using Common Voice (Ardila et al., 2020), the speech-transcription pairs of MUST-C V1.0 (Cattoni et al., 2021), and LibriSpeech (Panayotov et al., 2015). We evaluate our models on three multilingual ST benchmarks: MUST-C V1.0 (En → 8 lang.), COVOST 2 (Wang et al., 2020b) (En → 15 lang.), and FLEURS (Conneau et al., 2023) (En → 88 lang.) (Appendix A).

Model Architecture. The acoustic encoder follows WAV2VEC 2.0 LARGE (Baevski et al., 2020) with $N = 24$ layers and dimensionality $d = 1024$ (315M parameters). The CTC module uses a vocabulary with size $|\mathcal{V}| = 30$, and together with the acoustic encoder are initialized from a CTC-finetuned version of WAV2VEC 2.0 on LibriSpeech (Panayotov et al., 2015). The subword encoder has 3 layers with dimensionality of 1024 (35M). The text encoder has either $L = 12$ or $L = 24$, both with dimensionality 1024, and an embedding size of $|\mathcal{B}| = 256k$. We initialize its parameters from two dense versions of NLLB (NLLB et al., 2022), the 600M (MEDIUM) or the 1.3B (LARGE). Based on the size of NLLB, the resulting ZEROSWOT models used for inference have 0.95B (MEDIUM) or 1.65B (LARGE) parameters, while both of them the have the same number of training parameters (350M). We also train a SMALL version based on WAV2VEC 2.0 BASE (Appendix C.1).

Training details. We use AdamW (Loshchilov and Hutter, 2019) with a learning rate of 3e-4, inverse square root scheduler with warmup, and batch size of 32M tokens. We apply dropout of 0.1 as well as time and channel masking (Baevski et al., 2020). Speech input is 16kHz waveforms, and text is tokenzied with sentencepiece (Kudo and Richardson, 2018), using the NLLB model (Appendix C.2).

Loss. We set $\alpha = 0.9$ and apply Wasserstein losses for $\mathcal{I} = \{6, 7, 8, 9, 10, 11, 12\}$ (MEDIUM) and $\mathcal{I} = \{12, 14, 16, 18, 20, 22, 24\}$ (LARGE) (Eq. 17). Positional and entropy regularization are set to $\mu = 10$ (Eq. 14, 15), and $\lambda = 1$ (Eq. 16).

Evaluation. We apply checkpoint averaging and use a beam search of size 5. We evaluate with case-sensitive detokenized BLEU (Papineni et al., 2002) using sacreBLEU (Post, 2018) (Appendix B).

5 Results

MUST-C V1.0. In Table 2 we present the results of our proposed ZEROSWOT in MUST-C V1.0 and compare them with other SOTA zero-shot and supervised methods. We train ZEROSWOT under three conditions, regarding in-domain data:

(a) ASR✗/MT✗, where we use Common Voice.

(b) ASR✓/MT✗, where we use MUST-C^{ASR}.

(c) ASR✓/MT✓, with a multilingually finetuned NLLB on the MT data of MUST-C (App. D).

Our results in the upper part of Table 2 show that our SMALL model can surpass all previous zero-shot methods, even without using MT data from MUST-C, while also having less training parameters. Then, comparing to supervised methods, ZEROSWOT sets new SOTA in 7/8 directions, with multiple versions outperforming the previous best. Notably, ZEROSWOT-LARGE (c) is better in En-De and En-Es than the recently proposed LST (Zhang et al., 2023), which is based on LLaMA2-13B (Touvron et al., 2023), and compared to our method has $40\times$ / $8\times$ more training/inference parameters.

COVOST 2. In Table 3 we present the results of ZEROSWOT in COVOST 2, where we used Common Voice for training, and a finetuned NLLB on the MT data of COVOST En-X (Appendix D). For comparison, we provide results from other supervised SOTA methods (XLS-R (Babu et al., 2021), SEAMLESSM4T (SeamlessCommunication, 2023a,b)), and group them according to their size based on inference parameters. For the medium-sized models, we observe that although our method is evaluated on zero-shot ST and has less training parameters, it surpasses the previous SOTA SEAMLESSM4T by a large margin of 3.5 BLEU points on average and in 12/15 directions. For the large models, ZEROSWOT ranks better than the original LARGE configuration of SEAMLESSM4T, with an average of 31.1 BLEU, outperforming it by 0.6 points. Compared to the updated v2, our method is 0.5 BLEU points behind, but still obtains better results in 7/15 directions.

How does ZEROSWOT compare with cascades? To answer this, we train multilingual cascade ST systems based on WAV2VEC 2.0 and NLLB in MUST-C V1.0. The ASR system of the cascade can be either a CTC encoder or an attention-based encoder-decoder (AED), in which case we pair WAV2VEC 2.0 with a Transformer decoder (Appendix E). We group models by MUST-C data usage (as in Table 2) and by the size of NLLB, and also measure the average inference time per example. The results of Table 4 (extended at 10) highlight that although ZEROSWOT closely resembles a CTC-based cascade, in that it softly connects a CTC encoder and an MT model, its performance is consistently better, with gains from 4 to 7 BLEU points. This can be expected since CTC ASR models are error-prone, leading to compounding errors through the MT model (Bentivogli et al., 2021), where our method solves this by directly mapping the encoder representation to the MT embedding space. Compared to strong cascades that utilize AED ASR models, we observe that ZEROSWOT

Models		MuST-C Data		Train/Infer	BLEU								
		ASR	MT	Size (B)	De	Es	Fr	It	Nl	Pt	Ro	Ru	Average
Zero-shot End-to-End ST													
T-Modules (Duquenne et al., 2022)		✓	✗	2*	23.8	27.4	32.7	-	-	-	-	-	-
DCMA (Wang et al., 2022)		✓	✗	0.15*	22.4	24.6	29.7	18.4	22.0	24.2	16.8	11.8	21.2
DCMA (Wang et al., 2022)		✓	✓	0.15*	24.0	26.2	33.1	24.1	28.3	29.2	22.2	16.0	25.4
SimZeroCR (Gao et al., 2023b)		✓	✓	0.15*	25.1	27.0	34.6	-	-	-	-	15.6	-
ZeroSwot-Small	(b)	✓	✗	0.1/0.7	**27.3**	**31.7**	**35.8**	**26.8**	**30.9**	**31.6**	**25.3**	**17.8**	**28.4**
Supervised End-to-End ST													
Chimera (Han et al., 2021)			✓	0.15	27.1	30.6	35.6	25.0	29.2	30.2	24.0	17.4	27.4
STEMM (Fang et al., 2022)			✓	0.15*	28.7	31.0	37.4	25.8	30.5	31.7	24.5	17.8	28.4
SpeechUT (Zhang et al., 2022)			✓	0.15	30.1	33.6	41.4	-	-	-	-	-	-
Siamese-PT (Le et al., 2023)			✓	0.25*	27.9	31.8	39.2	27.7	31.7	34.2	27.0	18.5	29.8
CRESS (Fang and Feng, 2023)			✓	0.15*	29.4	33.2	40.1	27.6	32.2	33.6	26.4	19.7	30.3
SimRegCR (Gao et al., 2023b)			✓	0.15*	29.2	33.0	40.0	28.2	32.7	34.2	26.7	20.1	30.5
LST (LLaMA2-13B) (Zhang et al., 2023)			✓	13	30.4	35.3	**41.6**	-	-	-	-	-	-
Zero-shot End-to-End ST (this work)													
ZeroSwot-Medium	(a)	✗	✗	0.35/0.95	24.8	30.0	32.6	24.1	28.6	28.8	22.9	16.4	26.0
	(b)	✓	✗	0.35/0.95	28.5	33.1	37.5	28.2	32.3	32.9	26.0	18.7	29.6
	(c)	✓	✓	0.35/0.95†	30.5	34.9	39.4	30.6	35.0	37.1	27.8	20.3	31.9
ZeroSwot-Large	(a)	✗	✗	0.35/1.65	26.5	31.1	33.5	25.4	29.9	30.6	24.3	18.0	27.4
	(b)	✓	✗	0.35/1.65	30.1	34.8	38.9	29.8	34.4	35.3	27.6	20.4	31.4
	(c)	✓	✓	0.35/1.65†	**31.2**	**35.8**	40.5	**31.4**	**36.3**	**38.3**	**28.0**	**21.5**	**32.9**

Table 2: BLEU(↑) scores on MuST-C v1.0 `tst-COMMON`. Upper part: In **bold** best among previous zero-shot ST and our proposed (small) model. Lower part: Underscored is the best supervised score, highlighted are zero-shot scores that are better than the best supervised ones, and in **bold** is best overall. † NLLB parameters are finetuned separately. * Parameters estimated from methodology description. Extended results in Table 10.

Models	ZS	Size (B)	Ar	Ca	Cy	De	Et	Fa	Id	Ja	Lv	Mn	Sl	Sv	Ta	Tr	Zh	Average
Medium-sized models																		
XLS-R-1B	✗	1.0	19.2	32.1	**31.8**	26.2	22.4	21.3	30.3	39.9	22.0	14.9	25.4	32.3	18.1	17.1	36.7	26.0
SeamlessM4T-M	✗	1.2	20.8	37.3	29.9	**31.4**	23.3	17.2	34.8	37.5	19.5	12.9	29.0	37.3	18.9	**19.8**	30.0	26.6
ZeroSwot-M	✓	0.35/0.95	**24.4**	**38.7**	28.8	31.2	**26.2**	**26.0**	**36.0**	**46.0**	**24.8**	**19.0**	**31.6**	**37.8**	**24.4**	18.6	**39.0**	**30.2**
Large-sized models																		
XLS-R-2B	✗	2.0	20.7	34.2	33.8	28.3	24.1	22.9	32.5	41.5	23.5	16.2	27.6	34.5	19.8	18.6	38.5	27.8
SeamlessM4T-L	✗	2.3	24.5	41.6	33.6	35.9	28.5	19.3	39.0	39.4	23.8	15.7	35.0	42.5	22.7	23.9	33.1	30.6
↪ v2	✗	2.3	25.4	**43.6**	**35.5**	**37.0**	**29.3**	19.2	**40.2**	39.7	24.8	16.4	**36.2**	**43.7**	23.4	**24.7**	35.9	**31.7**
ZeroSwot-L	✓	0.35/1.65	**25.7**	40.0	29.0	32.8	27.2	**26.6**	37.1	**47.1**	**25.7**	**18.9**	33.2	39.3	**25.3**	19.8	**40.5**	31.2

Table 3: BLEU(↑) scores on CoVoST 2 En-X `test`. ZS stands for zero-shot ST. For ZeroSwot models, size is displayed in training/inference parameters. In **bold** are the best for each size category. Extended results in Table 12.

is noticeably better in the absence of in-domain data (a), while the cascade becomes slightly better when in-domain data become fully available (c). More importantly though, we find that ZeroSwot is more efficient, being 18% and 5% faster in the Medium and Large models accordingly.

Data Cond.	(a)		(b)		(c)		Time (sec)	
Model Size	M	L	M	L	M	L	M	L
Cascades with wav2vec 2.0 *based ASR model and NLLB*								
↪ CTC	21.8	24.7	25.4	27.5	24.7	26.5	**0.41**	**0.66**
↪ AED	25.2	26.5	**30.0**	31.1	**32.2**	**33.2**	0.56	0.82
ZeroSwot	**26.0** +0.8	**27.4** +0.9	29.6 -0.4	**31.4** +0.3	31.9 -0.3	32.9 -0.3	0.46 -18%	0.78 -5%

Table 4: Average BLEU(↑) scores and average inference Time(↓) in seconds on MuST-C v1.0 `tst-COMMON`.

Does our compression reduce the length gap? We replace our proposed compression adapter (§3.2.4), with either a length adaptor (Li et al., 2021) that down-samples by a factor of 4, or CTC compression (Gaido et al., 2021), or no compression at all (Appendix C.3). We also consider different types of tokenization than the proposed "Subword + Unk", which affect the placement of the separator tokens in the CTC target labels, and thus which representations are combined by the compression adapter. Apart from translation quality in MuST-C, we measure the length gap between the speech and text representations at the output of the shared encoder. Our findings in Table 5 show that given proper tokenization, our proposed adapter

Compression	Tokenization	BLEU	$\lvert\Delta\text{len}\rvert$	$r(\text{len})$
None	Word	28.9	267.6	10.9
Length Adaptor	Word	28.9	49.2	2.82
Character-level	Word	29.0	71.2	3.61
Compr. Adapter	Word	27.2	6.2	0.77
Compr. Adapter	Subword	28.4	3.3	0.88
Compr. Adapter	Subword + Unk	**29.6**	**1.4**	**0.98**

Table 5: Average BLEU(↑) scores, average absolute length difference $|\Delta\text{len}|$(↓), and average length ratio $r(\text{len})$ (closer to 1 is better), between compressed speech and text representations. Results with ZEROSWOT-MEDIUM (b) on MUST-C v1.0 `tst-COMMON`.

surpasses previous methods, by 0.6-0.7 points, and closes the length gap to an average of 1.4 tokens. We also find that without learning the text branch tokenzation, our compression falls behind previous methods. The length ratio of each method reveals that *over-compression*, i.e. $r(\text{len}) < 1$, is what worsens performance, leading to information loss, as even the model without compression, with $r(\text{len}) \approx 11$ achieves scores higher than our adapter with improper tokenization.

Does ZEROSWOT close the modality gap? Apart from the competitive zero-shot performance we provide further evidence by designing a cross-modal retrieval experiment. In Table 6 (left) we present the speech-text retrieval accuracy in the 2551 examples of MUST-C En-De `tst-COMMON`, and compare against ConST (Ye et al., 2022), which used contrastive learning. We retrieve either with cosine similarity (after temporal mean-pooling) or directly with Wasserstein distances. Our results show that ZEROSWOT with Wasserstein-based retrieval achieves an improvement of 3.5 points compared to ConST, approaching a perfect accuracy score[4], which highlights the degree of alignment between the representations.

Model	Acc.
ConST (Ye et al., 2022)	95.0
ZEROSWOT-M	98.1
↪ w/ Wass Retrieval	**98.5**

Model	BLEU
ZEROSWOT-M	**29.6**
↪ w/o Speech Emb.	28.6
↪ w/o Aux. Wass.	29.5

Table 6: Left: Speech-to-Text retrieval Accuracy(↑) on MUST-C v1.0 En-De `tst-COMMON`. Right: Average BLEU(↑) scores on MUST-C v1.0 `tst-COMMON`.

Is ZEROSWOT massively multilingual? We evaluate on FLEURS (Conneau et al., 2023), from English to 88 target languages. In Table 7 (left) we present the BLEU scores of ZEROSWOT trained on Common Voice, and additionally on MUST-C^{ASR} and LibriSpeech (More Data). Although our models are zero-shot ST systems, we find that they obtain results that are competitive to SEAMLESSM4T, which used 400k hours of audio data (Seamless-Communication, 2023a). We also find that ZEROSWOT is comparable to cascades, and that more ASR data can bring further improvements.

Model / Size	M	L
NLLB (MT)	22.5	24.8
Cascade ST	17.8	20.2
ZEROSWOT	18.1	20.1
↪ More Data	18.4	20.3
SEAMLESSM4T	**19.2**	**21.5**

ZEROSWOT Size (Scenario)	Type	
	ZS	FT
MEDIUM (b)	28.5	30.8
MEDIUM (c)	30.5	30.7
LARGE (b)	30.1	**32.0**
LARGE (c)	**31.2**	31.4

Table 7: Left: Average BLEU(↑) scores on FLEURS `test`. Right: BLEU(↑) scores of ST-finetuned ZEROSWOT models on MUST-C v1.0 En-De `tst-COMMON`.

Can ZEROSWOT benefit from ST finetuning? We experiment with the models trained on MUST-C^{ASR}, and finetune them using the paired ST data of MUST-C En-De. The results of Table 7 (right), our method with separate ASR and MT finetuning stages (scenario c) has already reached its limits, where further ST finetuning improves it only marginally. On the contrary, models trained only with ASR (scenario b) have still room for improvements with gains of 2 BLEU points, where ZEROSWOT-LARGE (b, FT) sets an even higher new SOTA for En-De at 32 BLEU points.

Ablations. In Table 6 (right) we observe that the speech embedder (§3.2.5) is critical to the effectiveness of ZEROSWOT, partly due to reasons regarding over-compression (absence of `<lang>` and `</s>`). Auxiliary Wasserstein losses have less impact, but are still beneficial.

6 Conclusions

We presented ZEROSWOT, a novel method for zero-shot end-to-end Speech Translation, that works by adapting a speech encoder to the representation space of a massively multilingual MT model. Our method sets new SOTA in MuST-C, while it also surpasses larger, supervised models in COVOST. We additionally showed that ZEROSWOT outperforms cascades, both in performance and efficiency. Finally, we provided evidence of closing the modality gap, with respect to both length and representation. Future research will expand on low-resource scenarios and speech-to-speech translation.

[4]Manual inspection of the 32 wrong predictions, showed that most of them are either due to many positives (several "Thank you.") or noisy examples (misaligned speech and text).

Limitations

Our method obtains state-of-the-art results in Speech Translation, despite being a zero-shot model. Still there are a couple of limitations inherent to the model, and on its evaluation. Although ZEROSWOT is an end-to-end model, in the sense that there is not intermediate transcription step and solves error-propagation, it suffers from some of the caveats of cascade systems. Since the speech encoder "mimics" the representation space of an MT model, no acoustic information is retained. This means that the resulting translation model can't use acoustic information, like prosody, and can thus be sometimes limited in each ability to carry out correct translations. Furthermore, given the requirement of ASR data to train the speech encoder, this methodology can't be used for spoken-only languages, at least in its current form.

Finally, in our evaluations we did not test for a different language, other than English, in the source. This was partly due to space constrains in the paper. Although we hypothesize that our proposed method can handle equally well other source languages, it would be interesting to be applied for low-resource scenarios, which we leave as future research.

References

Ashkan Alinejad and Anoop Sarkar. 2020. Effectively pretraining a speech translation decoder with Machine Translation data. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8014–8020, Online. Association for Computational Linguistics. [Cited on page 2.]

Sawsan Alqahtani, Garima Lalwani, Yi Zhang, Salvatore Romeo, and Saab Mansour. 2021. Using Optimal Transport as Alignment Objective for fine-tuning Multilingual Contextualized Embeddings. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 3904–3919, Punta Cana, Dominican Republic. Association for Computational Linguistics. [Cited on page 2.]

Antonios Anastasopoulos and David Chiang. 2018. Tied Multitask Learning for Neural Speech Translation. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 82–91, New Orleans, Louisiana. Association for Computational Linguistics. [Cited on pages 1 and 2.]

R. Ardila, M. Branson, K. Davis, M. Henretty, M. Kohler, J. Meyer, R. Morais, L. Saunders, F. M. Tyers, and G. Weber. 2020. Common voice: A massively-multilingual speech corpus. In *Proceedings of the 12th Conference on Language Resources and Evaluation (LREC 2020)*, pages 4211–4215. [Cited on page 5.]

Arun Babu, Changhan Wang, Andros Tjandra, Kushal Lakhotia, Qiantong Xu, Naman Goyal, Kritika Singh, Patrick von Platen, Yatharth Saraf, Juan Pino, et al. 2021. XLS-R: Self-supervised Cross-lingual Speech Representation Learning at Scale. *arXiv preprint arXiv:2111.09296*. [Cited on pages 6 and 18.]

Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli. 2020. wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations. In *Advances in Neural Information Processing Systems*, volume 33, pages 12449–12460. Curran Associates, Inc. [Cited on pages 2, 6, 15, 16, and 17.]

Sameer Bansal, Herman Kamper, Karen Livescu, Adam Lopez, and Sharon Goldwater. 2019. Pre-training on high-resource speech recognition improves low-resource speech-to-text translation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 58–68, Minneapolis, Minnesota. Association for Computational Linguistics. [Cited on page 2.]

Luisa Bentivogli, Mauro Cettolo, Marco Gaido, Alina Karakanta, Alberto Martinelli, Matteo Negri, and Marco Turchi. 2021. Cascade versus direct speech translation: Do the differences still make a difference? In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 2873–2887, Online. Association for Computational Linguistics. [Cited on page 6.]

Alexandre Bérard, Laurent Besacier, Ali Can Kocabiyikoglu, and Olivier Pietquin. 2018. End-to-End Automatic Speech Translation of Audiobooks. In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, page 6224–6228. IEEE Press. [Cited on pages 1 and 2.]

Alexandre Bérard, Olivier Pietquin, Laurent Besacier, and Christophe Servan. 2016. Listen and Translate: A Proof of Concept for End-to-End Speech-to-Text Translation. In *NIPS Workshop on end-to-end learning for speech and audio processing*, Barcelona, Spain. [Cited on page 1.]

Rishi Bommasani, Drew A. Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S. Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, Erik Brynjolfsson, Shyamal Buch, Dallas Card, Rodrigo Castellon, Niladri Chatterji, Annie Chen, Kathleen Creel, Jared Quincy Davis, Dora Demszky, Chris Donahue, Moussa Doumbouya, Esin Durmus, Stefano Ermon, John Etchemendy, Kawin Ethayarajh, Li Fei-Fei, Chelsea Finn, Trevor

Gale, Lauren Gillespie, Karan Goel, Noah Goodman, Shelby Grossman, Neel Guha, Tatsunori Hashimoto, Peter Henderson, John Hewitt, Daniel E. Ho, Jenny Hong, Kyle Hsu, Jing Huang, Thomas Icard, Saahil Jain, Dan Jurafsky, Pratyusha Kalluri, Siddharth Karamcheti, Geoff Keeling, Fereshte Khani, Omar Khattab, Pang Wei Koh, Mark Krass, Ranjay Krishna, Rohith Kuditipudi, Ananya Kumar, Faisal Ladhak, Mina Lee, Tony Lee, Jure Leskovec, Isabelle Levent, Xiang Lisa Li, Xuechen Li, Tengyu Ma, Ali Malik, Christopher D. Manning, Suvir Mirchandani, Eric Mitchell, Zanele Munyikwa, Suraj Nair, Avanika Narayan, Deepak Narayanan, Ben Newman, Allen Nie, Juan Carlos Niebles, Hamed Nilforoshan, Julian Nyarko, Giray Ogut, Laurel Orr, Isabel Papadimitriou, Joon Sung Park, Chris Piech, Eva Portelance, Christopher Potts, Aditi Raghunathan, Rob Reich, Hongyu Ren, Frieda Rong, Yusuf Roohani, Camilo Ruiz, Jack Ryan, Christopher Ré, Dorsa Sadigh, Shiori Sagawa, Keshav Santhanam, Andy Shih, Krishnan Srinivasan, Alex Tamkin, Rohan Taori, Armin W. Thomas, Florian Tramèr, Rose E. Wang, William Wang, Bohan Wu, Jiajun Wu, Yuhuai Wu, Sang Michael Xie, Michihiro Yasunaga, Jiaxuan You, Matei Zaharia, Michael Zhang, Tianyi Zhang, Xikun Zhang, Yuhui Zhang, Lucia Zheng, Kaitlyn Zhou, and Percy Liang. 2022. On the Opportunities and Risks of Foundation Models. [Cited on page 2.]

Roldano Cattoni, Mattia Antonino Di Gangi, Luisa Bentivogli, Matteo Negri, and Marco Turchi. 2021. MuST-C: A multilingual Corpus for End-to-end Speech Translation. *Computer Speech & Language*, 66:101155. [Cited on pages 2 and 5.]

Liqun Chen, Yizhe Zhang, Ruiyi Zhang, Chenyang Tao, Zhe Gan, Haichao Zhang, Bai Li, Dinghan Shen, Changyou Chen, and Lawrence Carin. 2019. Improving Sequence-to-Sequence Learning via Optimal Transport. In *International Conference on Learning Representations*. [Cited on page 2.]

Shun-Po Chuang, Tzu-Wei Sung, Alexander H. Liu, and Hung-yi Lee. 2020. Worse WER, but Better BLEU? Leveraging Word Embedding as Intermediate in Multitask End-to-End Speech Translation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5998–6003, Online. Association for Computational Linguistics. [Cited on page 2.]

Alexis Conneau, Min Ma, Simran Khanuja, Yu Zhang, Vera Axelrod, Siddharth Dalmia, Jason Riesa, Clara Rivera, and Ankur Bapna. 2023. FLEURS: FEW-Shot Learning Evaluation of Universal Representations of Speech. In *2022 IEEE Spoken Language Technology Workshop (SLT)*, pages 798–805. [Cited on pages 2, 5, and 8.]

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics. [Cited on pages 4 and 15.]

Tu Anh Dinh, Danni Liu, and Jan Niehues. 2022. Tackling Data Scarcity in Speech Translation Using Zero-Shot Multilingual Machine Translation Techniques. In *ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6222–6226. [Cited on page 3.]

Paul-Ambroise Duquenne, Hongyu Gong, Benoît Sagot, and Holger Schwenk. 2022. T-Modules: Translation Modules for Zero-Shot Cross-Modal Machine Translation. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5794–5806, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics. [Cited on pages 3, 7, and 19.]

Carlos Escolano, Marta R. Costa-jussà, José A. R. Fonollosa, and Mikel Artetxe. 2021a. Multilingual Machine Translation: Closing the Gap between Shared and Language-specific Encoder-Decoders. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 944–948, Online. Association for Computational Linguistics. [Cited on page 3.]

Carlos Escolano, Marta R. Costa-jussà, José A. R. Fonollosa, and Carlos Segura. 2021b. Enabling Zero-Shot Multilingual Spoken Language Translation with Language-Specific Encoders and Decoders. In *2021 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, pages 694–701. [Cited on pages 2 and 19.]

Qingkai Fang and Yang Feng. 2023. Understanding and Bridging the Modality Gap for Speech Translation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15864–15881, Toronto, Canada. Association for Computational Linguistics. [Cited on pages 7 and 19.]

Qingkai Fang, Rong Ye, Lei Li, Yang Feng, and Mingxuan Wang. 2022. STEMM: Self-learning with Speech-text Manifold Mixup for Speech Translation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7050–7062, Dublin, Ireland. Association for Computational Linguistics. [Cited on pages 1, 2, 7, and 19.]

Charlie Frogner, Chiyuan Zhang, Hossein Mobahi, Mauricio Araya-Polo, and Tomaso Poggio. 2015. Learning with a Wasserstein Loss. In *Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 2*, NIPS'15, page 2053–2061, Cambridge, MA, USA. MIT Press. [Cited on pages 1 and 5.]

Marco Gaido, Mauro Cettolo, Matteo Negri, and Marco Turchi. 2021. CTC-based Compression for Direct

Speech Translation. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 690–696, Online. Association for Computational Linguistics. [Cited on pages 2, 7, and 16.]

Marco Gaido, Mattia A. Di Gangi, Matteo Negri, and Marco Turchi. 2020. End-to-End Speech-Translation with Knowledge Distillation: FBK@IWSLT2020. In *Proceedings of the 17th International Conference on Spoken Language Translation*, pages 80–88, Online. Association for Computational Linguistics. [Cited on page 2.]

Gerard I. Gállego, Ioannis Tsiamas, Carlos Escolano, José A. R. Fonollosa, and Marta R. Costa-jussà. 2021. End-to-End Speech Translation with Pre-trained Models and Adapters: UPC at IWSLT 2021. In *Proceedings of the 18th International Conference on Spoken Language Translation (IWSLT 2021)*, pages 110–119, Bangkok, Thailand (online). Association for Computational Linguistics. [Cited on page 2.]

Pengzhi Gao, Liwen Zhang, Zhongjun He, Hua Wu, and Haifeng Wang. 2023a. Improving Zero-shot Multilingual Neural Machine Translation by Leveraging Cross-lingual Consistency Regularization. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 12103–12119, Toronto, Canada. Association for Computational Linguistics. [Cited on page 3.]

Pengzhi Gao, Ruiqing Zhang, Zhongjun He, Hua Wu, and Haifeng Wang. 2023b. An Empirical Study of Consistency Regularization for End-to-End Speech-to-Text Translation. [Cited on pages 3, 7, and 19.]

Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber. 2006. Connectionist Temporal Classification: Labelling Unsegmented Sequence Data with Recurrent Neural Networks. In *Proceedings of the 23rd International Conference on Machine Learning*, ICML '06, page 369–376, New York, NY, USA. Association for Computing Machinery. [Cited on pages 1 and 4.]

Chi Han, Mingxuan Wang, Heng Ji, and Lei Li. 2021. Learning shared semantic space for speech-to-text translation. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 2214–2225, Online. Association for Computational Linguistics. [Cited on pages 2, 7, and 19.]

Dan Hendrycks and Kevin Gimpel. 2020. Gaussian Error Linear Units (GELUs). [Cited on pages 15 and 17.]

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2022. LoRA: Low-rank adaptation of large language models. In *International Conference on Learning Representations*. [Cited on page 16.]

Sathish Indurthi, Mohd Abbas Zaidi, Nikhil Kumar Lakumarapu, Beomseok Lee, Hyojung Han, Seokchan Ahn, Sangha Kim, Chanwoo Kim, and Inchul Hwang. 2021. Task Aware Multi-Task Learning for Speech to Text Tasks. In *ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 7723–7727. [Cited on page 2.]

Ye Jia, Melvin Johnson, Wolfgang Macherey, Ron J. Weiss, Yuan Cao, Chung-Cheng Chiu, Naveen Ari, Stella Laurenzo, and Yonghui Wu. 2019. Leveraging Weakly Supervised Data to Improve End-to-end Speech-to-text Translation. In *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 7180–7184. [Cited on page 2.]

J. Kahn, M. Rivière, W. Zheng, E. Kharitonov, Q. Xu, P. E. Mazaré, J. Karadayi, V. Liptchinsky, R. Collobert, C. Fuegen, T. Likhomanenko, G. Synnaeve, A. Joulin, A. Mohamed, and E. Dupoux. 2020. Libri-light: A benchmark for asr with limited or no supervision. In *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 7669–7673. `https://github.com/facebookresearch/libri-light`. [Cited on page 15.]

Paul Knopp and Richard Sinkhorn. 1967. Concerning nonnegative matrices and doubly stochastic matrices. *Pacific Journal of Mathematics*, 21(2):343 – 348. [Cited on pages 5 and 16.]

Taku Kudo and John Richardson. 2018. SentencePiece: A simple and language independent subword tokenizer and detokenizer for Neural Text Processing. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 66–71, Brussels, Belgium. Association for Computational Linguistics. [Cited on pages 6 and 17.]

Tsz Kin Lam, Shigehiko Schamoni, and Stefan Riezler. 2022. Sample, Translate, Recombine: Leveraging Audio Alignments for Data Augmentation in End-to-end Speech Translation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 245–254, Dublin, Ireland. Association for Computational Linguistics. [Cited on page 2.]

Phuong-Hang Le, Hongyu Gong, Changhan Wang, Juan Pino, Benjamin Lecouteux, and Didier Schwab. 2023. Pre-training for Speech Translation: CTC Meets Optimal Transport. [Cited on pages 1, 2, 5, 7, and 19.]

Xian Li, Changhan Wang, Yun Tang, Chau Tran, Yuqing Tang, Juan Pino, Alexei Baevski, Alexis Conneau, and Michael Auli. 2021. Multilingual Speech Translation from Efficient Finetuning of Pretrained Models. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages

827–838, Online. Association for Computational Linguistics. [Cited on pages 1, 2, 7, and 16.]

Yuchen Liu, Hao Xiong, Jiajun Zhang, Zhongjun He, Hua Wu, Haifeng Wang, and Chengqing Zong. 2019. End-to-End Speech Translation with Knowledge Distillation. In *Proc. Interspeech 2019*, pages 1128–1132. [Cited on page 2.]

Yuchen Liu, Junnan Zhu, Jiajun Zhang, and Chengqing Zong. 2020. Bridging the Modality Gap for Speech-to-Text Translation. [Cited on pages 1, 2, 4, and 16.]

Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization. In *International Conference on Learning Representations*. [Cited on pages 6, 16, and 17.]

L. Mathias and W. Byrne. 2006. Statistical Phrase-Based Speech Translation. In *2006 IEEE International Conference on Acoustics Speech and Signal Processing Proceedings*, volume 1, pages I–I. [Cited on page 1.]

Nitika Mathur, Timothy Baldwin, and Trevor Cohn. 2020. Tangled up in BLEU: Reevaluating the Evaluation of Automatic Machine Translation Evaluation Metrics. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4984–4997, Online. Association for Computational Linguistics. [Cited on page 15.]

H. Ney. 1999. Speech translation: coupling of recognition and translation. In *1999 IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings. ICASSP99 (Cat. No.99CH36258)*, volume 1, pages 517–520 vol.1. [Cited on page 1.]

Team NLLB, Marta R. Costa-jussà, James Cross, Onur Çelebi, Maha Elbayad, Kenneth Heafield, Kevin Heffernan, Elahe Kalbassi, Janice Lam, Daniel Licht, Jean Maillard, Anna Sun, Skyler Wang, Guillaume Wenzek, Al Youngblood, Bapi Akula, Loic Barrault, Gabriel Mejia Gonzalez, Prangthip Hansanti, John Hoffman, Semarley Jarrett, Kaushik Ram Sadagopan, Dirk Rowe, Shannon Spruit, Chau Tran, Pierre Andrews, Necip Fazil Ayan, Shruti Bhosale, Sergey Edunov, Angela Fan, Cynthia Gao, Vedanuj Goswami, Francisco Guzmán, Philipp Koehn, Alexandre Mourachko, Christophe Ropers, Safiyyah Saleem, Holger Schwenk, and Jeff Wang. 2022. No Language Left Behind: Scaling Human-Centered Machine Translation. [Cited on pages 2, 3, 6, 15, and 17.]

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In *Proceedings of NAACL-HLT 2019: Demonstrations*. [Cited on pages 16 and 17.]

Siqi Ouyang, Rong Ye, and Lei Li. 2023. WACO: Word-Aligned Contrastive Learning for Speech Translation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3891–3907, Toronto, Canada. Association for Computational Linguistics. [Cited on page 2.]

Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur. 2015. Librispeech: An asr corpus based on public domain audio books. In *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 5206–5210. [Cited on pages 5, 6, and 15.]

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics. [Cited on pages 6 and 15.]

Gabriel Peyré and Marco Cuturi. 2019. Computational Optimal Transport: With Applications to Data Science. [Cited on pages 2 and 5.]

Juan Pino, Liezl Puzon, Jiatao Gu, Xutai Ma, Arya D. McCarthy, and Deepak Gopinath. 2019. Harnessing Indirect Training Data for End-to-End Automatic Speech Translation: Tricks of the Trade. In *Proceedings of the 16th International Conference on Spoken Language Translation*, Hong Kong. Association for Computational Linguistics. [Cited on page 2.]

Matt Post. 2018. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191, Belgium, Brussels. Association for Computational Linguistics. [Cited on pages 6 and 15.]

Seamless-Communication. 2023a. SeamlessM4T—Massively Multilingual & Multimodal Machine Translation. *ArXiv*. [Cited on pages 2, 6, 8, and 18.]

Seamless-Communication. 2023b. Seamless: Multilingual Expressive and Streaming Speech Translation. [Cited on page 6.]

Matthias Sperber and Matthias Paulik. 2020. Speech Translation and the End-to-End Promise: Taking Stock of Where We Are. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7409–7421, Online. Association for Computational Linguistics. [Cited on page 1.]

Yun Tang, Hongyu Gong, Ning Dong, Changhan Wang, Wei-Ning Hsu, Jiatao Gu, Alexei Baevski, Xian Li, Abdelrahman Mohamed, Michael Auli, and Juan Pino. 2022. Unified Speech-Text Pre-training for Speech Translation and Recognition. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1488–1499, Dublin, Ireland. Association for Computational Linguistics. [Cited on pages 2 and 19.]

Yun Tang, Juan Pino, Xian Li, Changhan Wang, and Dmitriy Genzel. 2021a. Improving Speech Translation by Understanding and Learning from the Auxiliary Text Translation Task. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4252–4261, Online. Association for Computational Linguistics. [Cited on page 2.]

Yun Tang, Juan Pino, Changhan Wang, Xutai Ma, and Dmitriy Genzel. 2021b. A General Multi-Task Learning Framework to Leverage Text Data for Speech to Text Tasks. In *ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6209–6213. [Cited on page 2.]

Yuqing Tang, Chau Tran, Xian Li, Peng-Jen Chen, Naman Goyal, Vishrav Chaudhary, Jiatao Gu, and Angela Fan. 2020. Multilingual Translation with Extensible Multilingual Pretraining and Finetuning. [Cited on page 2.]

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open Foundation and Fine-Tuned Chat Models. [Cited on pages 2 and 6.]

Ioannis Tsiamas, José A. R. Fonollosa, and Marta R. Costa-jussà. 2022a. SegAugment: Maximizing the Utility of Speech Translation Data with Segmentation-based Augmentations. [Cited on page 2.]

Ioannis Tsiamas, Gerard I. Gállego, Carlos Escolano, José Fonollosa, and Marta R. Costa-jussà. 2022b. Pretrained Speech Encoders and Efficient Finetuning Methods for Speech Translation: UPC at IWSLT 2022. In *Proceedings of the 19th International Conference on Spoken Language Translation (IWSLT 2022)*, pages 265–276, Dublin, Ireland (in-person and online). Association for Computational Linguistics. [Cited on page 2.]

Ioannis Tsiamas, Gerard I. Gállego, Jose Fonollosa, and Marta R. Costa-jussá. 2023. Speech Translation with Foundation Models and Optimal Transport: UPC at IWSLT23. In *Proceedings of the 20th International Conference on Spoken Language Translation (IWSLT 2023)*, pages 397–410, Toronto, Canada (in-person and online). Association for Computational Linguistics. [Cited on pages 1, 2, and 5.]

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc. [Cited on page 3.]

Changhan Wang, Yun Tang, Xutai Ma, Anne Wu, Dmytro Okhonko, and Juan Pino. 2020a. Fairseq S2T: Fast speech-to-text modeling with fairseq. In *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing: System Demonstrations*, pages 33–39, Suzhou, China. Association for Computational Linguistics. [Cited on pages 2 and 16.]

Changhan Wang, Anne Wu, and Juan Pino. 2020b. CoVoST 2: A Massively Multilingual Speech-to-Text Translation Corpus. [Cited on pages 2 and 5.]

Chen Wang, Yuchen Liu, Boxing Chen, Jiajun Zhang, Wei Luo, Zhongqiang Huang, and Chengqing Zong. 2022. Discrete Cross-Modal Alignment Enables Zero-Shot Speech Translation. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5291–5302, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics. [Cited on pages 3, 7, and 19.]

Ruibin Xiong, Yunchang Yang, Di He, Kai Zheng, Shuxin Zheng, Chen Xing, Huishuai Zhang, Yanyan Lan, Liwei Wang, and Tie-Yan Liu. 2020. On layer normalization in the transformer architecture. In *Proceedings of the 37th International Conference on Machine Learning*, ICML'20. JMLR.org. [Cited on pages 15 and 17.]

Chen Xu, Bojie Hu, Yanyang Li, Yuhao Zhang, Shen Huang, Qi Ju, Tong Xiao, and Jingbo Zhu. 2021a. Stacked acoustic-and-textual encoding: Integrating the pre-trained models into speech translation encoders. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 2619–2630, Online. Association for Computational Linguistics. [Cited on page 2.]

Qiantong Xu, Alexei Baevski, Tatiana Likhomanenko, Paden Tomasello, Alexis Conneau, Ronan Collobert, Gabriel Synnaeve, and Michael Auli. 2021b. Self-training and pre-training are complementary for

speech recognition. In *ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 3030–3034. [Cited on page 15.]

Rong Ye, Mingxuan Wang, and Lei Li. 2021. End-to-End Speech Translation via Cross-Modal Progressive Training. In *Proc. Interspeech 2021*, pages 2267–2271. [Cited on pages 1 and 2.]

Rong Ye, Mingxuan Wang, and Lei Li. 2022. Cross-modal Contrastive Learning for Speech Translation. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 5099–5113, Seattle, United States. Association for Computational Linguistics. [Cited on pages 1, 2, 8, and 19.]

Hao Zhang, Nianwen Si, Yaqi Chen, Wenlin Zhang, Xukui Yang, Dan Qu, and Xiaolin Jiao. 2023. Tuning Large language model for End-to-end Speech Translation. [Cited on pages 2, 6, 7, and 19.]

Ziqiang Zhang, Long Zhou, Junyi Ao, Shujie Liu, Lirong Dai, Jinyu Li, and Furu Wei. 2022. SpeechUT: Bridging Speech and Text with Hidden-Unit for Encoder-Decoder Based Speech-Text Pre-training. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 1663–1676, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics. [Cited on pages 7 and 19.]

Jinming Zhao, Hao Yang, Gholamreza Haffari, and Ehsan Shareghi. 2022. RedApt: An Adaptor for wav2vec 2 Encoding Faster and Smaller Speech Translation without Quality Compromise. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 1960–1967, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics. [Cited on page 2.]

Yan Zhou, Qingkai Fang, and Yang Feng. 2023. CMOT: Cross-modal Mixup via Optimal Transport for Speech Translation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7873–7887, Toronto, Canada. Association for Computational Linguistics. [Cited on pages 2 and 19.]

A Data Processing and Filtering

Dataset	Size		Average Length	
	examples	hours	speech	text
LibriSpeech	281K	961	12.3	46.6
Common Voice	949K	1,503	5.7	17.2
MuST-C^{ASR}	352K	681	7.0	29.7

Table 8: Dataset statistics for Siamese training. Speech length is measured in seconds, and text length in tokens.

A.1 MuST-C v1.0

For the `train` set of each language pair, we perform text cleaning on both the transcription and translation, including space and punctuation normalization as well as removal of non-utf characters. We also remove speaker names and events such as "(Laughing)". Following, we remove examples that contain less than 4 characters, or have a transcription-to-translation ratio smaller than 0.5 or larger than 2. For the siamese training we remove the translations, and process the transcriptions by replacing numbers and symbols with their spelled out forms. Then we concatenate all eight training sets and remove duplicates according to the triplet of (*speaker*, *text*, *duration*). Due to alignment errors during the creation of the dataset, the same text can be paired with different parts of audio for different language pairs. Thus, for duplicates of (*speaker*, *text*) we keep the example that is closer to the speaking ratio of speaker[5]. Finally, we remove examples with extreme words-per-second ratio (larger than 10). A summary of the dataset sizes is available at Table 9. We also similarly construct a validation set, with a total of 2,081 examples, to be used during training, by concatenating the individual `dev` sets (without filtering), and simple removal of hard duplicates according to the triplet of (*speaker*, *text*, *duration*).

Dataset	Examples (K)	Hours
En-De	220	384
En-Es	254	473
En-Fr	262	466
En-It	242	438
En-Nl	237	416
En-Pt	196	359
En-Ro	226	406
En-Ru	250	458
MuST-C^{ASR}	1,888	3,402
↪ Duplicate removal	367	713
↪ Speaking ratio filtering	353	681

Table 9: Number of examples (in thousands) and total duration of MuST-C v1.0 `train` set used to train ZeroSwot.

[5]Calculated as the average words-per-second of all the examples for this speaker in the concatenated dataset.

A.2 Common Voice

We use version 8.0[6], and more specifically the `train` and `dev` splits. For the `train` split, we apply text normalization, as well as replace numbers and symbols with their spelled-out forms.

A.3 LibriSpeech

For training we use the `train-clean-100`, `train-clean-360`, and `train-other-500` splits, and for evaluation the `dev-clean` one. Since LibriSpeech has normalized transcriptions, we restore the casing and punctuation with a finetuned BERT-base model (Devlin et al., 2019) using rpunct.[7]

A.4 CTC Labels

For all the datasets, to obtain the target labels for CTC, first we tokenize the transcription with the NLLB sentencepiece model[8], then remove casing, replace all spaces with the <sep> token, and substitute all characters not present in the WAV2VEC 2.0 letter-based vocabulary[9] with the <unk> token.

B Evaluation

The evaluation of all models, either MT, ZEROSWOT, ASR, Cascade ST, or Supervised ST remains the same. We apply checkpoint averaging to the 10 best checkpoints according to the corresponding validation metric, and generate with a beam search of 5. We measure translation quality with BLEU (Papineni et al., 2002) using sacreBLEU (Post, 2018) with signature `BLEU|nrefs:1|case:mixed|eff:no|tok:13a|smooth:exp|version:2.3.1`. For comparing with SEAMLESSM4T, we follow their evaluation, and using a `char` tokenization for Mandarin Chinese, Japanese, Thai, Lao and Burmese. We do not carry statistical significance testing since in almost all results we are comparing average BLEU scores across many language directions. Although BLEU as a metric has its limitations (Mathur et al., 2020), we opted to use it for comparison with previous methods from the literature.

C ZEROSWOT Models

C.1 Model Architecture

The acoustic encoder is composed of a feature extractor with 7 strided convolutional layers that sub-sample the signal by $r = 320$, followed by $N = 24$ transformer layers with $d = 1024$ (Baevski et al., 2020). Each layer has feed-forward dimension of 4096, 16 attention heads, GELU activations (Hendrycks and Gimpel, 2020), and use the pre-layernorm configuration (Xiong et al., 2020). The acoustic encoder and the linear layer of the CTC with size $|\mathcal{V}| = 30$ are initialized from a large version of WAV2VEC 2.0[10], with around 315M parameters, which was pretrained with self-supervised learning and self training (Xu et al., 2021b), and finetuned on ASR with Librispeech (Panayotov et al., 2015) and Libri-light (Kahn et al., 2020).

The subword encoder in the compression adapter is a Transformer encoder with 3 layers and dimensionality $d = 1024$, which have the same format as the ones in the acoustic encoder. We also add sinusoidal positional encodings to the chunked input.

The text embedding uses a vocabulary with size $|\mathcal{B}| = 256k$, and for the text encoder we are either using the MEDIUM version with $L = 12$ layers or the LARGE version with $L = 24$ layers. Each layer in the MEDIUM version has a dimensionality of 1024, feed-forward dimension of 4096, ReLU activation, 16 attention heads, and pre-layernorm configuration. The only difference of the LARGE version apart from the number of layers is the feed-forward dimension which is 8192. For initialization we are using two dense versions of NLLB (NLLB et al., 2022), which have been distilled from the 54B parameter sparse model: the 600M version[11] and the 1.3B version[12].

The SMALL version of our method uses the BASE[13] version of WAV2VEC 2.0 (12 layers and dimensionality 768) and NLLB-MEDIUM. The subword encoder has 3 layers, with dimensionality 768. We use a linear layer to project its output to the $d = 1024$, which is the dimensionality of the text encoder due to NLLB-MEDIUM. The total number of training parameters is 110M, while the inference parameters are approximately 0.7B.

[6] commonvoice.mozilla.org/en/datasets
[7] github.com/Felflare/rpunct
[8] fairseq/nllb/flores200_sacrebleu_tokenizer_spm.model
[9] fairseq/wav2vec/dict.ltr.txt
[10] fairseq/wav2vec/wav2vec_vox_960h_pl.pt
[11] fairseq/nllb/nllb-200-distilled-600M.pt
[12] fairseq/nllb/nllb-200-distilled-1.3B.pt
[13] fairseq/wav2vec/wav2vec_small_960h_pl.pt

C.2 Training details

We finetune the parameters of the acoustic encoder, CTC module and compression adapter, while the parameters of the speech embedder, text embedding and text encoder are kept frozen. We are using AdamW (0.9, 0.98) (Loshchilov and Hutter, 2019) with a base learning rate of 3e-4, an inverse square root scheduler with a linear warmup (2k for MuST-C^{ASR}, 4k for Common Voice), and a batch size 32M tokens. The input to the speech branch is raw waveforms sampled at 16kHz and the input to the text branch is English text, tokenized with the NLLB sentencepiece model[14].

For the Wasserstein loss we are using the geomloss package[15] using the Sinkhorn distance (Knopp and Sinkhorn, 1967) with the default parameters. When it for multiple layers, we batch them together for efficient computation. The Wasserstein losses for the intermediate layers are applied after the first layer-norm of the next layer, since we are using a pre-layernorm setting. Applying the losses on representations that have not been layernormed made the training unstable.

We use an activation dropout of 0.1 in the acoustic encoder, a dropout of 0.1 in the CTC module, and a dropout of 0.1 in the compression adapter. We furthermore apply masking to the speech signal (Baevski et al., 2020), with a probability of 0.3 to mask 10 consecutive frames, and a probability of 0.2 to mask 64 consecutive frequency channels.

To speed-up the training, we extract offline the text encoder representations from NLLB, and can thus completely remove the frozen text branch during the training of the speech encoder.

We train until convergence, and apply early stopping if the Wasserstein loss of the last layer in the development set using has not improved for 10 epochs. Models on LibriSpeech or MuST-C^{ASR} usually train for around 50k steps, while on Common Voice they train for around 150k.

To accelerate the training for models in Common Voice, we trained a *seed* model using the original MEDIUM version of NLLB, and then adapted the resulting speech encoder to different NLLB versions (LARGE and/or finetuned). For adaptation, only required 30k steps (compared to 150k of the seed model), where we used learning of 3e-5, warm-up of 1k steps and cosine annealing.

All models are implemented and trained on FAIRSEQ (Ott et al., 2019; Wang et al., 2020a) with `memory-efficient-fp16`. Training for 50k steps takes around 36 hours on a machine with 8 NVIDIA 3090s (for either MEDIUM or LARGE).

[14] fairseq/nllb/flores200_sacrebleu_tokenizer_spm.model
[15] kernel-operations.io/geomloss

C.3 Models trained with different type of compression

Here we provide details for the models trained to obtain the results of Table 5. To ensure a fair comparison we keep the same number of parameters for all models, by adding transformer layers or MLPs. Architecture changes are done only in the part of the compression, and everything else remains the same (including Speech Embedder). For the model without compression we add two large MLPs with residual connections at the output of the acoustic encoder. The MLPs consist of up-projection to 8192, GELU activation, and down-projection back to 1024. For the model with the Length Adaptor (Li et al., 2021), we use 2 strided convolutional layers that sub-sample the output of the acoustic encoder by a factor of 4, followed by a transformer layer. For the model using CTC-based compression (Liu et al., 2020; Gaido et al., 2021) we first mean-pool consecutive same-labeled representations as in §3.2.4, followed by 3 transformer layers. For the models using the proposed compression adapter but different tokenizations, we just change the CTC target labels, and everything else remains the same.

C.4 Supervised ST finetuning

Here we provide details for the ST-finetuned versions of ZEROSWOT from Table 7 (right). We train for 20k steps with a learning rate of 4e-5, linear warmup for 1k steps, fixed for another 4k steps, and reduced with cosine annealing for the rest. For MEDIUM models we finetune the parameters of the compression adapter, text encoder and text decoder, and thus keep frozen the acoustic encoder, speech embedder, and text embedding. For the LARGE models, we only finetune the compression adapter and apply LNA to the text encoder-decoder (Li et al., 2021). We hypothesize that better results could be obtain with more sophisticated finetuning approaches (Hu et al., 2022) For inference we average the 10 best checkpoints according to BLEU on MuST-C v1.0 En-De dev.

D Machine Translation Models

Model Architecture. For the MT models used in this research we used NLLB-600M (MEDIUM)

and NLLB-1.3B (LARGE), which are dense transformers distilled from a 54B parameter Mixture-of-Experts (MoE) model (NLLB et al., 2022). NLLB supports many-to-many translation between 202 languages. The MEDIUM model has 12 layers in both encoder and decoder, model dimensionality of 1024, feed-forward dimension of 4096, 16 attention heads, ReLU activations, and using pre-layernorm (Xiong et al., 2020). The only difference of the LARGE model is that has 24 layers in both encoder and decoder, and a feed-forward dimension of 8192. Both use a multilingual shared vocabulary of 256k tokens learned with sentencepiece (Kudo and Richardson, 2018).

Finetuning hyperparameters. In order to adapt them to the domain and languages of MUST-C V1.0 and COVOST 2, we did multilingual finetuning of NLLB using their transcription-translation pairs. We used batch size of 32k tokens for the MEDIUM, and 64k for LARGE. We used the AdamW optimizer (Loshchilov and Hutter, 2019) with 2k warm-up updates and an inverse square root scheduler. The learning rate and dropout rate were selected from a grid search to {7.5e-5, 1e-4, **2e-4**} and {0.1, 0.2, **0.3**} accordingly[16]. We also use a dropout of 0.1 for the attention, 0.0 for the activations and a label smoothing of 0.1 for the cross entropy loss, as was done for training the original versions (NLLB et al., 2022). We evaluate every 500 steps on the `dev` sets, and early stop if the loss has not improved for 20 consecutive evaluations. At the end of the training we average the best 10 checkpoints according to the `dev` sets loss. Models were trained with `fp16`, while to train the LARGE version on an NVIDIA 3090, we used `memory-efficient-fp16` (Ott et al., 2019). Models in MUST-C V1.0 required 40k steps to converge, while the ones in COVOST 2 required around 100k.

Results. BLEU scores for both the original and finetuned versions are available at Table 10 for MUST-C V1.0 and Table 12 for COVOST 2.

E Cascade Speech Translation Models

Here we provide the training details and hyperparameters used for the Cascade ST systems (Table 4). For the MT models we used either NLLB-MEDIUM or NLLB-LARGE, which were optionally finetuned, as described in Appendix D. For the ASR models we either used CTC or attention-based encoder-decoder (AED) models, as described below.

CTC ASR Models. The architecture is the same with the acoustic encoder used in the ZEROSWOT models, followed by a CTC module (Appendix C). We initialize the model with the same version used to initialize the ZEROSWOT models, and finetune it with CTC on either MUST-C^{ASR} or Common Voice. For each dataset, we use exactly the same filtering and preprocessing (Appendix A), and as targets for the CTC we use the standard labeling (Table 1, 1st row). We use AdamW (Loshchilov and Hutter, 2019) with a learning rate of 1e-4, warmup of 1k steps and an inverse square root scheduler, and the batch size is set to 32M tokens. We use a dropout of 0.1 for the activations and at the CTC module, and a time masking with probability 0.5 for length of 10, and channel masking with probability of 0.25 for size of 64 (Baevski et al., 2020). We evaluate every 250 steps and stop the training when the validation loss did not improve for 10 consecutive evaluations. We average the 10 best checkpoints according to the validation loss. The size of the model is around 315 million parameters. Results for these models are available at Table 11.

AED ASR Models. The architecture of the encoder is the same as with the CTC ASR model. For the decoder we use 6 transformer layers with dimensionality of 768, feed-forward dimension of 3072, 8 attention heads, GeLU activations (Hendrycks and Gimpel, 2020), and pre-layernorm (Xiong et al., 2020). We initialize the encoder with a pretrained WAV2VEC 2.0[17], train the whole model with cross entropy using LibriSpeech and then finetune it either on MUST-C^{ASR} or Common Voice. The target vocabulary has a size of 16k and is learned jointly on the three ASR datasets with sentencepiece. For each dataset, we use exactly the same filtering and preprocessing (Appendix A), and the target text is the same we used for training the ZEROSWOT models. The hyperparameters are the same for both training on LibriSpeech and finetuning on MUST-C^{ASR} or Common Voice. We use AdamW (Loshchilov and Hutter, 2019) with learning rate of 2e-4, an inverse square root scheduler with a warmup of 1k steps, and a batch size of 32M tokens. The masking and dropout for the encoder are as in the CTC model, while for the decoder we use a dropout of 0.1, and a label smoothing of 0.1. We evaluate every 500 steps and stop training when

[16] For each NLLB version we run 9 experiment in MUST-C V1.0 and used the optimal combinations also for COVOST 2.

[17] fairseq/wav2vec/wav2vec_vox_new.pt

the validation loss did not improve for 10 consecutive updates. We average the 10 best checkpoints according to the validation loss. The size of the model is around 390 million parameters. Results for these models are available at Table 11.

Cascade ST inference. For generation, we use a beam search of size 5 for either the CTC or AED ASR model, and then pass the ASR generated text to the MT model, which generates the translation with a beam search of size 5.

F Detailed Results in MuST-C v1.0

In Table 10 we provide a summary of all obtained results in MuST-C v1.0, with our ZeroSwot models (including ablations), our cascade models, and our finetuned NLLB models. We also provide more results from the literature for both zero-shot and supervised ST models. Note on performance drop of CTC-based Cascade when moving from the original NLLB model (scenarios b) to the finetuned one (scenarios c). We hypothesize that the original NLLB can better handle the noisy English text produces by the CTC ASR model, due to the abundance of data it was trained on. When finetuning it using the bitext of MuST-C v1.0, the model losses some of this capacity.

In Table 11 we provide the results in MuST-C v1.0 of the ASR models we trained for the CTC-based and AED-based cascades (Tables 4, 10). Models trained on Common Voice correspond to scenario (a), while models trained on MuST-C v1.0 correspond to scenarios (b, c).

G Detailed Results in CoVoST 2

Here we provide a more extended version of Table 3, including MT results of NLLB (original & finetuned), ZeroSwot results with the original NLLB, and also add XLS-R-0.3B (Babu et al., 2021).

H Detailed Results in FLEURS

In Table 13 we present the per-language[18] results for FLEURS En-X test. ZeroSwot is trained on Common Voice, while "+ More Data" indicates that it was additionally trained on MuST-C^{ASR} and LibriSpeech. NLLB results are obtained by us, by running the original versions, while SeamlessM4T (Seamless-Communication, 2023a) results are obtained from their repository[19].

[18] github.com/openlanguagedata/flores
[19] facebookresearch/seamless_communication

Models		MuST-C Data		Training/Inferece Params (B)	BLEU								
		ASR	MT		De	Es	Fr	It	Nl	Pt	Ro	Ru	Average
Machine Translation													
NLLB-MEDIUM (original, used in a, b)		-	✗	0.6	32.7	36.9	45.2	32.2	36.0	37.4	30.3	21.0	34.0
NLLB-MEDIUM-MUST-C (ours, used in c)		-	✓	0.6	34.4	38.8	44.6	34.7	39.0	41.6	32.1	22.4	35.9
NLLB-LARGE (original, used in a, b)		-	✗	1.3	34.6	38.6	46.8	33.7	38.2	39.6	31.8	23.2	35.8
NLLB-LARGE-MUST-C (ours, used in c)		-	✓	1.3	35.3	39.9	45.8	36.0	40.6	43.1	32.6	23.9	37.2
(Other works) Zero-shot End-to-End Speech Translation													
MultiSLT (Escolano et al., 2021b)		✓	✓	0.05	6.8	6.8	10.9	-	-	-	-	-	-
T-Modules (Duquenne et al., 2022)		✓	✗	2	23.8	27.4	32.7	-	-	-	-	-	-
DCMA (Wang et al., 2022)		✓	✗	0.15	22.4	24.6	29.7	18.4	22.0	24.2	16.8	11.8	21.2
DCMA (Wang et al., 2022)		✓	✓	0.15	24.0	26.2	33.1	24.1	28.3	29.2	22.2	16.0	25.4
SimZeroCR (Gao et al., 2023b)		✓	✓	0.15	25.1	27.0	34.6	-	-	-	-	15.6	-
(Ours) Zero-shot End-to-End Speech Translation													
ZEROSWOT-SMALL (w2v-BASE and NLLB-MEDIUM)	(b)	✓	✗	0.1 / 0.7	27.0	31.6	35.6	26.6	30.9	31.5	25.1	17.9	28.3
ZEROSWOT-MEDIUM (w2v-LARGE and NLLB-MEDIUM)	(a)	✗	✗	0.35 / 0.95	24.8	30.0	32.6	24.1	28.6	28.8	22.9	16.4	26.0
	(b)	✓	✗	0.35 / 0.95	28.5	33.1	37.5	28.2	32.3	32.9	26.0	18.7	29.6
	(c)	✓	✓	0.35 / 0.95	30.5	34.9	39.4	30.6	35.0	37.1	27.8	20.3	31.9
ZEROSWOT-LARGE (w2v-LARGE and NLLB-LARGE)	(a)	✗	✗	0.35 / 1.65	26.5	31.1	33.5	25.4	29.9	30.6	24.3	18.0	27.4
	(b)	✓	✗	0.35 / 1.65	30.1	34.8	38.9	29.8	34.4	35.3	27.6	20.4	31.4
	(c)	✓	✓	0.35 / 1.65	31.2	35.8	40.5	31.4	36.3	38.3	28.0	21.5	32.9
(Ours) Cascaded Speech Translation with CTC ASR model													
WAV2VEC 2.0 and NLLB-MEDIUM	(a)	✗	✗	(0.3 + 0.6) / 0.9	21.9	24.4	27.5	19.3	23.7	24.0	19.8	14.2	21.8
	(b)	✓	✗	(0.3 + 0.6) / 0.9	26.1	28.1	32.6	22.9	27.9	27.9	23.5	16.6	25.7
	(c)	✓	✓	(0.3 + 0.6) / 0.9	25.1	26.8	30.1	20.9	27.6	28.5	20.7	17.8	24.7
WAV2VEC 2.0 and NLLB-LARGE	(a)	✗	✗	(0.3 + 1.3) / 1.6	24.7	27.1	30.3	21.6	26.8	27.4	22.9	16.9	24.7
	(b)	✓	✗	(0.3 + 1.3) / 1.6	27.8	29.9	34.4	24.6	29.6	30.0	25.6	18.5	27.5
	(c)	✓	✓	(0.3 + 1.3) / 1.6	27.0	28.4	31.9	22.6	29.5	31.4	22.1	19.0	26.5
(Ours) Cascaded Speech Translation with Attention-based Encoder-Decoder ASR model													
w2v-Transformer and NLLB-MEDIUM	(a)	✗	✗	(0.4 + 0.6) / 1	24.3	27.9	33.2	23.0	27.0	27.2	22.5	16.7	25.2
	(b)	✓	✗	(0.4 + 0.6) / 1	29.0	32.6	39.8	27.9	32.0	32.9	27.1	18.9	30.0
	(c)	✓	✓	(0.4 + 0.6) / 1	31.1	34.4	41.4	30.2	34.7	37.2	28.3	20.6	32.2
w2v-Transformer and NLLB-LARGE	(a)	✗	✗	(0.4 + 1.3) / 1.7	25.8	29.0	34.5	24.4	28.7	27.5	23.6	18.2	26.5
	(b)	✓	✗	(0.4 + 1.3) / 1.7	30.8	33.5	41.6	29.4	33.2	33.3	28.1	20.2	31.3
	(c)	✓	✓	(0.4 + 1.3) / 1.7	32.0	35.3	42.5	31.2	36.0	38.4	28.8	21.6	33.2
(Other works) Supervised End-to-End Speech Translation													
Chimera (Han et al., 2021)			✓	0.15	27.1	30.6	35.6	25.0	29.2	30.2	24.0	17.4	27.4
STEMM (Fang et al., 2022)			✓	0.15	28.7	31.0	37.4	25.8	30.5	31.7	24.5	17.8	28.4
ConST (Ye et al., 2022)			✓	0.15	28.3	32.0	38.3	27.2	31.7	33.1	25.6	18.9	29.4
STPT (Tang et al., 2022)			✓	0.15	29.2	33.1	39.7	-	-	-	-	-	-
SpeechUT (Zhang et al., 2022)			✓	0.15	30.1	33.6	41.4	-	-	-	-	-	-
CMOT (Zhou et al., 2023)			✓	0.15	29.0	32.8	39.5	27.5	32.1	33.5	26.0	19.2	30.0
Siamese-PT (Le et al., 2023)			✓	0.25	27.9	31.8	39.2	27.7	31.7	34.2	27.0	18.5	29.8
CRESS (Fang and Feng, 2023)			✓	0.15	29.4	33.2	40.1	27.6	32.2	33.6	26.4	19.7	30.3
SimRegCR (Gao et al., 2023b)			✓	0.15	29.2	33.0	40.0	28.2	32.7	34.2	26.7	20.1	30.5
LST (LLaMA2-7B) (Zhang et al., 2023)			✓	7 / 7.3	29.2	33.1	40.8	-	-	-	-	-	-
LST (LLaMA2-13B) (Zhang et al., 2023)			✓	13 / 13.3	30.4	35.3	41.6	-	-	-	-	-	-
(Ours) Experiments on Compression with ZEROSWOT-MEDIUM *(b) from Table 5*													
Without Compression		✓	✗	0.35 / 0.95	27.6	33.0	36.4	27.4	31.5	32.0	25.2	18.2	28.9
Length Adaptor (down-sampling ×4)		✓	✗	0.35 / 0.95	27.8	32.4	36.7	27.9	31.4	31.6	25.4	18.3	28.9
Character-level Compression		✓	✗	0.35 / 0.95	27.9	32.6	36.9	27.8	31.8	31.4	25.4	18.1	29.0
Compr. Adapter + Word Tokenization		✓	✗	0.35 / 0.95	26.4	31.0	33.7	25.7	29.6	30.3	24.1	17.3	27.2
Compr. Adapter + Subword Tokenization		✓	✗	0.35 / 0.95	27.3	32.5	35.4	26.4	31.0	31.6	25.0	18.3	28.4
(Ours) Ablations with ZEROSWOT-MEDIUM *(b) from Table 6 (right)*													
Without Speech Embedder		✓	✗	0.35 / 0.95	27.2	32.6	36.0	27.1	31.3	31.9	25.1	17.9	28.6
WIthout Auxiliary Wasserstein Losses		✓	✗	0.35 / 0.95	28.4	33.1	37.3	27.9	32.3	32.6	25.9	18.6	29.5

Table 10: Extended Results on MUST-C v1.0 `tst-COMMON`.

Models	Type	ASR Data	Training Params (B)	WER								
				De	Es	Fr	It	Nl	Pt	Ro	Ru	Average
w2v	CTC	Common Voice	0.3	42.5	42.5	42.5	42.6	42.6	42.6	42.5	42.5	42.5
w2v	CTC	MuST-C v1.0	0.3	21.4	21.4	21.4	21.4	21.4	21.5	21.5	21.5	21.4
w2v-Transformer	AED	Common Voice	0.4	20.4	20.9	20.5	20.7	20.3	21.1	20.8	20.6	20.7
w2v-Transformer	AED	MuST-C v1.0	0.4	9.8	10.1	9.8	10.0	9.6	10.6	10.2	9.9	10.0

Table 11: ASR Results on MuST-C v1.0 `tst-COMMON`. AED stands for attention-based encoder-decoder.

Models	Size (B)	Ar	Ca	Cy	De	Et	Fa	Id	Ja	Lv	Mn	Sl	Sv	Ta	Tr	Zh	Average
Machine Translation																	
NLLB-M (original)	0.6	20.0	39.0	26.3	35.5	23.4	15.7	39.6	21.8	14.8	10.4	30.3	41.1	20.2	21.1	34.8	26.3
NLLB-M-CoVoST (ours)	0.6	28.5	46.3	35.5	37.1	31.5	29.2	45.2	38.4	29.1	22.0	37.7	45.4	29.9	23.0	46.7	35.0
NLLB-L (original)	1.3	23.3	43.5	33.5	37.9	27.9	16.6	41.9	23.0	20.0	13.1	35.1	43.8	21.7	23.8	37.5	29.5
NLLB-L-CoVoST (ours)	1.3	29.9	47.8	35.6	38.8	32.7	29.9	46.4	39.5	29.9	21.7	39.3	46.8	31.0	24.4	48.2	36.1
(Ours) Zero-shot End-to-End Speech Translation																	
ZeroSwot-M	0.35 / 0.95	17.6	32.5	18.0	29.9	20.4	16.3	32.4	32.0	13.3	10.0	25.2	34.4	17.8	15.6	30.5	23.1
↪ NLLB-M-CoVoST	0.35 / 0.95	24.4	38.7	28.8	31.2	26.2	26.0	36.0	46.0	24.8	19.0	31.6	37.8	24.4	18.6	39.0	30.2
ZeroSwot-L	0.35 / 1.65	19.8	36.1	22.6	31.8	23.6	16.8	34.2	33.6	17.5	11.8	28.9	36.8	19.1	17.5	32.2	25.5
↪ NLLB-L-CoVoST	0.35 / 1.65	25.7	40.0	29.0	32.8	27.2	26.6	37.1	47.1	25.7	18.9	33.2	39.3	25.3	19.8	40.5	31.2
(Other works) Supervised End-to-End Speech Translation																	
XLS-R-0.3B	0.3	16.3	28.7	29.1	23.6	19.6	19.0	27.4	36.9	19.3	13.2	22.4	29.1	15.6	15.0	33.5	23.2
XLS-R-1B	1.0	19.2	32.1	31.8	26.2	22.4	21.3	30.3	39.9	22.0	14.9	25.4	32.3	18.1	17.1	36.7	26.0
XLS-R-2B	2.0	20.7	34.2	33.8	28.3	24.1	22.9	32.5	41.5	23.5	16.2	27.6	34.5	19.8	18.6	38.5	27.8
SeamlessM4T-M	1.2	20.8	37.3	29.9	31.4	23.3	17.2	34.8	37.5	19.5	12.9	29.0	37.3	18.9	19.8	30.0	26.6
SeamlessM4T-L	2.3	24.5	41.6	33.6	35.9	28.5	19.3	39.0	39.4	23.8	15.7	35.0	42.5	22.7	23.9	33.1	30.6
↪ v2	2.3	25.4	43.6	35.5	37.0	29.3	19.2	40.2	39.7	24.8	16.4	36.2	43.7	23.4	24.7	35.9	31.7

Table 12: Extended Results on CoVoST 2 `test`.

Language Code	MEDIUM					LARGE				
	NLLB	**Cascade**	**ZEROSWOT**	**+ More Data**	**SEAMLESSM4T**	**NLLB**	**Cascade**	**ZEROSWOT**	**+ More Data**	**SEAMLESSM4T**
amh-Ethi	12.2	9.2	9.9	10.0	10.0	13.2	11.5	9.4	9.4	12.2
arb-Arab	23.1	18.1	18.7	18.9	20.0	26.4	20.5	21.2	21.9	22.9
asm-Beng	6.8	4.9	6.6	6.7	6.0	6.8	6.2	7.1	6.7	6.7
azj-Latn	11.0	8.3	8.7	8.6	9.2	13.2	10.2	10.4	10.4	11.0
bel-Cyrl	11.3	8.7	8.3	8.5	8.6	13.3	10.2	9.5	9.9	10.3
ben-Beng	14.8	12.0	13.5	13.7	13.2	17.6	13.6	15.0	15.2	15.1
bos-Latn	26.9	20.8	20.9	21.7	24.3	31.2	23.2	24.5	25.4	26.8
bul-Cyrl	36.7	29.4	29.8	30.7	30.4	40.4	33.4	33.2	33.5	35.5
cat-Latn	37.1	28.6	30.6	30.7	32.7	40.4	32.0	33.6	34.2	35.8
ceb-Latn	28.6	22.2	21.6	22.2	21.6	29.6	25.0	22.2	22.3	22.2
ces-Latn	28.4	21.1	20.7	21.7	22.6	30.2	24.6	23.3	24.4	24.8
ckb-Arab	8.3	5.7	7.5	7.7	8.2	10.8	7.7	8.3	8.5	10.0
zho-Hans	28.2	27.1	24.4	24.9	25.8	31.7	30.2	26.1	25.4	29.8
cym-Latn	33.2	25.3	26.2	26.7	33.7	41.5	32.4	33.0	33.4	37.4
dan-Latn	40.3	32.8	33.9	34.4	34.7	42.5	35.9	35.6	36.1	39.2
deu-Latn	34.8	28.1	27.7	28.7	28.6	37.4	31.2	31.0	31.4	32.5
ell-Grek	24.0	20.0	20.4	20.7	19.4	26.5	22.2	22.5	23.0	22.0
est-Latn	18.4	14.2	14.1	14.7	17.6	23.4	18.9	18.5	18.4	21.0
fin-Latn	18.3	13.9	14.0	14.4	15.8	22.6	18.2	18.5	19.0	20.3
fra-Latn	46.2	37.7	35.5	36.3	37.4	48.7	40.4	37.4	38.3	41.4
fuv-Latn	1.2	0.3	0.5	0.6	0.7	2.3	0.4	1.0	1.1	0.7
gaz-Latn	3.4	1.9	1.7	1.7	2.8	3.9	3.2	2.0	2.0	4.9
gle-Latn	22.5	16.6	17.0	17.7	20.7	27.4	21.0	21.1	21.3	23.4
glg-Latn	30.9	24.7	25.3	25.8	27.1	33.5	26.5	27.4	28.1	29.0
guj-Gujr	22.1	16.9	17.6	17.8	17.7	23.4	18.1	18.4	18.4	19.7
heb-Hebr	24.2	18.9	19.3	19.9	19.6	29.3	23.4	24.3	24.2	24.9
hin-Deva	29.7	24.7	24.6	25.3	27.1	30.8	26.5	25.8	26.0	28.8
hrv-Latn	23.7	18.3	18.9	19.0	21.0	28.8	21.2	22.8	23.2	22.8
hun-Latn	21.1	15.8	16.4	16.5	16.7	24.4	19.7	19.3	19.8	19.7
hye-Armn	15.9	13.1	14.7	15.2	14.8	17.9	15.1	17.1	17.1	16.2
ibo-Latn	15.6	13.1	11.6	11.7	13.6	16.7	14.5	12.0	11.9	13.8
ind-Latn	42.3	30.8	31.9	32.4	33.7	44.7	33.2	34.2	34.4	36.8
isl-Latn	19.5	14.1	14.7	15.2	15.6	22.3	17.7	16.8	17.0	20.6
ita-Latn	28.0	21.5	22.1	22.4	21.9	29.1	22.6	23.2	23.7	23.9
jav-Latn	25.5	16.9	17.8	17.8	19.8	28.0	19.1	19.4	19.6	20.4
jpn-Jpan	34.1	31.6	30.5	30.8	31.9	36.2	34.3	32.9	33.3	35.6
kan-Knda	17.7	13.1	13.4	13.6	13.5	19.4	14.3	14.3	14.2	15.2
kat-Geor	13.0	10.4	9.9	9.8	9.8	14.0	11.1	10.6	10.7	12.1
kaz-Cyrl	18.8	14.6	14.3	14.5	15.5	20.9	17.3	15.8	15.4	18.8
khk-Cyrl	9.1	6.9	7.5	7.7	9.8	11.4	9.4	9.5	9.7	12.2
khm-Khmr	0.8	0.1	2.5	2.7	0.7	1.4	0.4	2.6	2.8	0.4
kir-Cyrl	12.3	9.0	9.2	9.6	9.8	13.0	10.5	10.1	10.2	11.4
kor-Hang	12.0	9.2	9.8	10.1	10.4	12.2	11.5	10.8	10.7	11.7
lao-Laoo	54.3	49.4	53.1	53.0	54.5	56.1	53.3	54.7	54.8	55.2
lit-Latn	19.0	14.1	14.0	14.2	16.1	22.1	18.1	16.8	16.9	19.0
lug-Latn	6.6	3.6	3.6	3.4	6.4	8.6	5.2	4.9	5.0	6.8
luo-Latn	10.8	7.2	7.4	7.5	9.6	11.2	8.4	8.2	8.1	9.2
lvs-Latn	18.1	14.5	15.2	15.5	20.1	23.2	19.7	19.8	19.9	23.0
mal-Mlym	14.2	10.4	9.8	9.8	11.0	14.7	13.0	10.7	10.7	13.3
mar-Deva	13.6	10.2	10.8	10.7	11.4	16.1	11.8	12.0	12.4	13.0
mkd-Cyrl	28.9	23.5	23.7	23.5	26.5	33.3	27.4	26.9	27.2	28.8
mlt-Latn	24.2	20.9	14.8	14.6	24.0	28.8	24.0	18.0	18.0	27.6
mya-Mymr	41.4	43.1	40.4	40.3	41.5	43.3	45.8	43.1	43.3	43.0
nld-Latn	25.3	19.9	20.8	21.2	21.7	26.6	20.7	22.6	22.8	24.2
nob-Latn	30.8	24.7	25.0	25.6	26.8	33.2	26.4	26.3	27.1	28.5
npi-Deva	16.7	12.7	13.2	13.3	15.3	16.9	14.1	13.1	13.5	15.7
nya-Latn	14.3	9.6	9.2	9.1	10.4	14.2	10.9	9.6	10.1	10.8
ory-Orya	14.2	11.3	12.3	12.4	12.6	15.6	13.5	12.5	12.5	13.5
pan-Guru	22.6	17.7	18.8	19.5	19.5	24.4	19.0	21.1	21.1	21.7
pbt-Arab	12.7	10.5	10.9	11.0	11.1	13.8	10.4	11.4	11.5	11.6
pes-Arab	21.7	17.4	22.5	22.9	18.3	23.2	19.6	23.5	24.3	21.1
pol-Latn	18.3	13.6	13.6	14.1	14.6	20.4	15.9	15.9	16.2	16.9
por-Latn	45.5	37.0	37.5	38.2	38.0	47.0	39.2	39.4	40.0	40.5
ron-Latn	33.5	28.0	26.1	26.4	29.3	35.6	32.0	27.8	28.4	31.9
rus-Cyrl	27.5	21.7	22.1	22.3	22.1	29.8	24.2	24.6	25.2	25.8
slk-Latn	27.8	21.0	21.5	21.7	22.6	32.3	25.1	25.4	25.7	27.1

slv-Latn	23.3	17.6	18.1	18.7	19.4	26.0	20.6	21.6	22.0	23.2
sna-Latn	11.4	6.7	6.4	6.8	5.8	11.8	6.9	6.8	6.4	6.7
snd-Arab	19.4	16.3	17.1	17.5	18.9	21.0	17.1	18.3	18.0	18.0
som-Latn	11.2	8.4	8.0	8.0	8.5	12.1	8.8	8.7	8.6	9.7
spa-Latn	27.5	21.7	22.1	22.9	21.1	27.7	22.4	22.9	23.2	23.9
srp-Cyrl	27.6	22.2	21.9	22.8	26.8	32.6	26.2	26.3	27.2	30.3
swe-Latn	40.7	32.0	33.2	34.1	34.0	44.0	35.2	36.2	36.6	38.4
swh-Latn	31.6	24.8	23.6	23.8	26.2	32.7	27.0	24.8	24.7	27.9
tam-Taml	16.2	11.8	11.8	12.4	13.3	18.6	14.0	13.2	13.9	15.4
tel-Telu	21.1	15.2	15.3	15.3	17.4	24.1	17.1	17.4	17.3	19.4
tgk-Cyrl	18.6	14.2	14.9	15.1	0.1	22.0	17.3	17.2	17.7	0.1
tgl-Latn	30.5	22.7	23.5	23.7	26.1	33.7	24.8	26.0	26.4	28.0
tha-Thai	47.7	46.7	46.5	46.5	49.8	51.1	50.0	49.5	49.9	51.2
tur-Latn	23.1	16.5	17.5	18.0	19.4	27.4	20.4	21.1	21.4	22.6
ukr-Cyrl	23.0	18.5	19.0	18.8	20.8	26.9	22.0	22.3	22.2	24.8
urd-Arab	21.3	18.0	18.4	18.7	18.9	23.2	19.6	20.4	20.6	20.6
uzn-Latn	14.3	11.3	11.3	11.0	12.8	17.2	13.5	13.6	13.6	14.6
vie-Latn	38.1	31.3	32.2	32.6	32.7	40.8	33.6	34.4	35.0	35.1
yor-Latn	3.7	3.1	3.2	3.0	4.4	5.0	2.1	4.2	3.8	4.5
zho-Hant	0.5	0.1	1.2	1.2	0.2	0.6	0.2	1.2	1.2	0.3
zsm-Latn	37.2	28.1	28.1	28.7	21.5	40.6	30.7	30.2	30.4	34.2
zul-Latn	16.2	11.1	11.0	11.4	11.9	18.7	11.4	12.2	12.3	13.4
Average	22.5	17.8	18.1	18.4	19.2	24.8	20.2	20.1	20.3	21.5

Table 13: Extended Results on FLEURS `test`.